Three Essays on Asset Management and Financial Institutions

by

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Abstract

In Chapter 1, we investigate the role of mutual fund flows in incorporating market sentiment into asset prices. We show that retail investors adjust their investments among mutual fund categories in response to changes in market sentiment. Consistent with sentiment-induced price pressure through fund flows, we further find that firms favored by mutual funds, such as large-cap, dividend payers, and firms with high institutional ownership are most sensitive to market sentiment. We construct a pricing factor representing sentiment risk and find that the sentiment factor is significant in standard asset pricing models and robust to various sorting procedures.

In Chapter 2, we investigate the role of in-house meetings with corporate insiders in shaping institutional investors' portfolios. Using taxi trips that occur between NYC mutual funds and NYC public firms as a proxy for in-house meetings, we find that mutual funds with more local taxi trips tend to exhibit greater local bias and that these funds outperform their non-NYC peers on their investment in NYC equities. These effects are larger for small, undiversified, and old funds that are better at monitoring local information. We further explore the information content of taxi trips by focusing on earnings announcement. Our findings suggest that taxi trips are more likely to occur in the second week before announcement dates and that the number of taxi trips that a firm received is negatively associated with earnings surprises.

In Chapter 3, we investigate how banks respond to natural disasters and whether they could benefit from these events. Natural disasters are not rare and costless events. Indeed, the evidence indicates there has been an acceleration in the number of disasters and the associated costs over the past century. Such disasters can cause severe property damages in the communities affected. Typically, insurance policies and government disaster relief fail to cover the full amount of damages. In this case, banks/branches can play an important supporting role in providing additional funding for the necessary reconstruction that takes place after disasters. In our paper, we demonstrate that following natural disasters, the affected branches raise both deposit and loan rates, but the latter more than the former so that the banks' net interest margin increases. This, in turn, leads to an increase in return on assets for such banks. At the same time, the impact of natural disasters on banks causes such banks to increase the use of brokered deposits to help fund the increased demand for loans by individuals and firms in affected communities. This suggests that overall the impact of natural disasters is beneficial to banks located in the disaster-prone areas.

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List of Abbreviations

ASR	Advisors' Sentiment Report
AUM	Asset Under Management
BD	Brokered Deposits-to-Total Deposits
BWI	Baker and Wurgler Sentiment Index
CMA	Conservative Minus Aggressive (Investment Factor)
CPI	Consumer Price Index
CRSP	The Center for Research in Security Prices
FDIC	Federal Deposit Insurance Corporation
FHV	For Hire Vehicle
FOIA	Freedom of Information Act
GMS	Geomagnetic Storm
HHI	Herfindahl-Hirschman Index
HML	High Minus Low (Value Factor)
ICI	Investment Company Institute
INF	Informed
LINF	Less Informed
MOM	Momentum Factor
MRP	Market Risk Premium
NIM	Net Interest Margin
NYC	New York City
RMW	Robust Minus Week (Profitability Factor)
ROA	Return on Assets
SENT	Sentiment Factor
SHELDUS	Spatial Hazard Event Loss for the United States
SMB	Small Minus Big (Size Factor)
SSC	Storm Sudden Commencement
SUE	Standardized Unexpected Earnings
PDD	Presidential Disaster Declarations
TLC	NYC Taxi and Limousine Commission
TNA	Total Net Asset
UMD	Up Minus Down (Momentum Factor)

Chapter 1
The Role of Market Sentiment in Asset Allocations and Stock Returns

1.1 Introduction

Prior studies on market sentiment document that stocks with high retail concentrations, i.e., small, young or financially distressed stocks, and stocks with low institutional ownership, are disproportionately more sensitive to shifts in market sentiment (See, among others, Baker and Wurgler (2006), Lee, Shleifer and Thaler (1991), Lemmon and Portniaguina (2006), Kumar and Lee (2006), Du and Hu (2018)). A key assumption in these studies is that retail investors are more likely to be affected by market sentiment and that they demand more (less) risky assets as they become more bullish (bearish). Consequently, "lottery-like" stocks are more sensitive to sentiment-induced demand shocks, while "bond-like" stocks are less driven by sentiment (Baker and Wurgler (2007)).

The past decades, however, have witnessed a shift of household investments from direct stock holdings to indirect holdings. French (2008) documents that the household direct holdings of U.S. corporate equities shrunk steadily from 47.9% in 1980 to 21.5% in 2007. Meanwhile, the indirect holdings through mutual funds grew dramatically from 4.6% to 32.4%. According to the Investment Company Fact Book (2016), the total assets managed by mutual funds totaled nearly $16 trillion at year-end 2015, and households held 89% of all mutual fund assets and 95% of all long-term assets. Therefore, mutual fund flows may represent an important but underreported channel for sentiment effect to manifest itself in asset prices.

In this paper, we propose that "bond-like" stocks are also affected by the sentiment effect through mutual fund flows. We argue that, in addition to direct stock trading, retail investors also adjust their investments across different fund categories in response to sentiment shocks. These sentiment-driven fund flows cause price pressure on equities held in the fund portfolios, which are primarily large, often more mature firms.

This sentiment-based temporary price pressure hypothesis has two predictions. First, firms favored by mutual funds are sensitive to market sentiment. Considering that most equity funds hold primarily "bond-like" stocks, it is not surprising that these stocks may be strongly affected by market sentiment. Second, the price impact of sentiment-driven flows is short-lived. Prior research has shown that flow-driven returns are reversed subsequently (Ben-Rephael, Kandel and Wohl (2011, 2012)). It should be even more so for sentiment-induced flows because sentiment might fluctuate due to non-fundamental signals that contain no information about future earnings. Precisely, we expect the sentiment effect to result in only short-term mispricing, but not to affect the long-term equilibrium.

To evaluate the role of fund flows in sentiment effect, we conduct a two-step analysis. First, we investigate whether individual investors adjust their investments among different mutual fund classes in response to change in market sentiment. We employ U.S. mutual fund flows and exchanges data at fund category level. We find that change in market sentiment is positively associated with net flows to equity funds but negatively associated with net flows to money market funds. We conduct further tests for domestic equity funds with both net flows and net exchanges. The results indicate that aggressive funds are the most sensitive to shifts in market sentiment. For other domestic funds, i.e., growth, growth and income, and income funds, the sentiment effect is weaker, though still significant.

These results are consistent with the literature in both psychology and economics that studies the relation between mood and risk-preference. For example, Carton et al. (1992) find that depressed subjects have lower sensation-seeking scores than normal subjects, indicating higher risk aversion. Felton, Gibson and Sanbonmatsu (2003) find differences in investment decisions of males with different levels of optimism. Gibson and Sanbonmatsu (2004) show the effect of optimism on risk taking in gambling situations. Other studies (Harmatz et al. (2000), Kramer and Weber (2012) and Bassi, Colacito and Fulghieri (2013)) show the effect of seasonal depressive mood on individual risk preferences.

Our findings show that a one-standard-deviation increase in market sentiment is associated with an increase in net flows of roughly 47.5 basis points to equity funds. In percentage terms, this seems rather small, but in dollar terms it is equivalent approximately to $14 billion. This sudden inflow of capital into mutual funds creates considerable buying pressure for assets held in their portfolios. Some recent studies have shown that fund flows result in temporary price impact that is reversed later. For example, Coval and Stafford (2007) find that flow-driven purchases and sales exert significant price pressure in equity markets, resulting in transaction prices far from fundamental value. Ben-Rephael, Kandel and Wohl (2011) study the relationship between net daily mutual fund flows and the returns of the Tel Aviv 25 index (the index of 25 largest stocks in Israel). They conclude that a shock to fund flows is related to a positive contemporaneous price impact that is subsequently reversed. Maher, Brown and Kumar (2008) investigates the effect of unexpected flows on valuation of the individual firms. They find that unexpected net flows have significant effect on valuation effect.

Second, we empirically examine the effect of sentiment-induced temporary price pressure on equities. We create a market sentiment factor (SENT) similar to the momentum factor built in Carhart (1997) and test its significance in explaining returns of portfolios sorted on various characteristics. We find that the SENT factor is significant when added to standard asset pricing models. Its significance persists across various model settings and is robust to a variety of sorting procedures. The average risk premium of SENT factor is not significantly different from zero. This suggests that SENT factor captures only temporary mispricing that is reversed in the long run. This is consistent with our second prediction.

Our study contributes to the literature in several ways. First, our paper adds to the literature that investigates the relation between risk preference and asset allocation decisions. Prior studies either document a flight-to-quality behavior of retail investors in the context of extreme events or exogenous shocks, like fire sales and terrorist attacks (Zeng (2017) and Wang and Young (2016)), or use mutual fund flows directly as a proxy for market sentiment (Warther (1995), Indro (2004), and Ben-Rephael, Kandel and Wohl (2012)). In contrast, our study focuses on normal times and quantifies the influence of a marginal change in sentiment on retail investors' asset allocation decisions.

Second, our study contributes to the fast-growing body of literature on the flow-driven price impact (See Gompers and Metrick (2001), Coval and Stafford (2007), Ben-Rephael et al. (2011)), and Lou (2012)). We find that firms that are more sensitive to market sentiment have greater volatility and that the sentiment factor is significant in explaining excess stock returns across multiple model settings. We, however, do not find long-lasting risk premium associated with the sentiment factor. These results are consistent with prior literature and support the rationale that sentiment-induced price impact through mutual fund flows is only temporary.

Finally, our study complements the existing literature on the role of market sentiment in asset pricing. While prior research builds on noise trader model and explores the influence of sentiment through the direct stock trading channel (Antoniou, Doukas and Subrahmanyam (2016), Baker and Wurgler (2006), Baker, Wurgler and Yuan (2012), Brown and Cliff (2004), Chen et al.

(2014), Du and Hu (2018), Kaplanski and Levy (2010), Kumar and Lee (2006), Lemmon and Portniaguina (2006), Neal and Wheatley (1998), Stambaugh, Yu and Yuan (2012), Stambaugh and Yuan (2016), and Tetlock (2007)), our study investigates the price implication of sentiment fluctuations through the mutual fund flow channel. Our contribution with this regard is twofold. First, we extend the research of market sentiment to the stocks heavily held by institutions, which constitute more than 80% of total market capital and are presumed to be immune from sentiment. We show that these stocks, large stocks with large institutional ownership in particular, have positive significant loadings on the sentiment factor. Second, we show that though market sentiment is price destabilizing in short-term, it doesn't affect the long-term equilibrium.

1.2 Data

We obtain data from several sources. We obtain monthly data on aggregate fund flows from the Investment Company Institute (ICI). ICI reports flow data for 33 mutual fund objective categories from January 1984 to December 2014. For each fund category, ICI reports the aggregated value of sales, redemptions, exchanges in, exchanges out, reinvestment distributions, and total net assets. We follow Kamstra et al. (2017) to group the 33 fund categories into equity, hybrid, corporate, municipal, government bonds, and finally money market fund classes. We calculate normalized monthly net flows to fund category *i* as follows:

$$NetFlows_{i,t} = \frac{Sales_{i,t} - Redemptions_{i,t} + ExchangesIn_{i,t} - ExchangesOut_{i,t}}{TotalNetAssets_{i,t-1}}. \quad (1)$$

We consider net exchanges as an alternative measure of net flows. ICI define exchange as the dollar value of mutual fund shares switched into or out of funds and into other funds within the same fund family. Since net exchanges are exempt from some confounding factors like liquidity constraints and long-term saving plans, they are more likely to reflect investor sentiment than net sales and redemptions and represent a clearer view of the sentiment-driven trades of retail investors (Ben-Rephael et al. (2012) and Kamstra et al. (2017)). Thus, if the investment decisions of retail investors are influenced by sentiment, we expect the effect to manifest in both net flows and net exchanges. We compute net exchanges as follows:

$$NetExchanges_{i,t} = \frac{ExchangesIn_{i,t} - ExchangesOut_{i,t}}{TotalNetAssets_{i,t-1}}. \tag{2}$$

Panel A of Table 1.1 reports summary statistics of the aggregate fund flows and macroeconomic control variables. Panel B describes flows in detail for each fund class. Prior studies, such as Warther (1995) and Griffin, Nardari and Stulz (2004) find that net flows are autoregressive, so we report the results of partial correlations in columns (5) – (8). Among all six asset classes, equity, hybrid, and corporate fixed income are AR(3) processes, while municipal fixed income, government fixed income, and money market funds are AR(4) processes. All autocorrelations vanish within four lags, consistent with existing literature.

--------------- Insert Table 1.1 ---------------

We obtain monthly stock returns, shares outstanding, trading volume, and returns on the S&P 500 from CRSP over 1967 – 2014. Our sample contains only ordinary common equities (share codes 10 and 11). To be included in the sample, a firm must have at least four-year's history in CRSP. Further, it must have fewer than 24 missing values from its previous 48 monthly returns before June every year, when we rebalance portfolios. This mitigates any issues related to survivorship bias inherent in CRSP for performance-related delisted firms, as stated by Shumway (1997), and Shumway and Warther (1999), and enables us to measure correlations over a meaningful period. The criteria limits the number of firms available in our sample data to 15,276. Firm-level financial data come from the Compustat standardized databases of Global Market Intelligence. Following Fama and French (1992), we merge Compustat's firm-level data with the data from CRSP, using CUSIP, ticker, and company name variables. A firm's stock returns for the period from July of year t to June of year t+1 are matched and merged with its accounting data for the fiscal year ending in year t–1.

Data for the total institutional holdings and ownership concentration, measured by the Herfindahl-Hirschman Index (HHI), come from the Thomson Reuters (13F) database. We obtain the monthly returns on factor portfolios—market risk premium (MRP), size factor (SMB), value factor (HML), profitability factor (RMW), investment factor, (CMA), momentum factor (MOM), and risk-free rates—from 1967 to 2014 from Kenneth R. French's data library.

1.3 Sentiment Measure

The most cited sentiment measure in the past decade is constructed by Baker and Wurgler (2006). By taking the first principal component, their novel measure aggregates the common information in six sentiment proxies: closed-end fund discount, lagged NYSE share turnover, number of IPOs, lagged average first-day returns on IPOs, equity share in new issues, and lagged dividend premium. However, as discussed by Baker and Wurgler in the description of their online data library, this sentiment index is not designed for measuring changes in sentiment due to the lag structure and low frequency of some sentiment proxies.

In this paper we use the weekly Advisors' Sentiment Report (ASR) provided by Investors Intelligence. For every week, Investor Intelligence studies more than a hundred market newsletters and assesses each author's attitude toward the market movement as bullish, bearish, or correction (neutral). We compute the ratio of the number of bullish advisors over the sum of bullish and bearish advisors as our investor sentiment proxy. We choose to build our sentiment measure based on the Advisors' Sentiment Report because (1) the report summarizes the advisor's expectations about the future market performance, (2) these expectations are based on all information available at the time of reporting, including fundamental as well as non-fundamental information, and (3) the report is widely publicized in, for example, NY Times, Barrons or Investor's Business Daily.

Lee, Jiang, and Indro (2002) argue that ASR proxies for retail investor sentiment. The reason is that, though the newsletters are written by financial advisors, the primary target of financial advisory services are retail investors. Compared to institutional investors, retail investors lack timely information and formal training to conduct security analysis, their trading is more likely to be influenced by the recommendation made in the advisors' report and their sentiment is also more likely to be affected by change in advisors' sentiment. Sirri and Tufano (1998) show that funds with greater marketing fees and media cites in financial press experience faster growth, suggesting that retail investors are susceptible to recommendation made by financial advisors.

Market sentiment is influenced by fundamental factors as well as non-fundamental factors that have no direct influence on future cash flows. Some of these non-fundamental factors suggested in prior literature include, for example, losses in soccer matches (Edmans, García and Norli (2007)), aviation disasters (Kaplanski and Levy (2010)), terrorist attacks (Young and Wang (2016)), construction starts of skyscrapers (Löffler (2003)), and even solar activities (Raps, Stoupel and Shimshoni (1992) and Kay (1994)).

To verify the validity of our sentiment measure, we conduct various correlation analyses between ASR and fundamental and non-fundamental variables. First, we obtain data on three composite economic indexes from Bloomberg. The set of indexes is assembled by the Conference Board and consists of lagging, coincident, and leading economic indexes. The leading, coincident, and lagging economic indexes are essentially composite averages of several individual leading, coincident, or lagging economic indicators. All components are averaged and standardized for the purpose of equalizing volatility. We estimate the pairwise correlations between ASR, economic indexes, and growth in the indexes. For comparison, we also show the correlations with the orthogonalized Baker and Wurgler Sentiment Index (BWI). The results, as reported in Panel A of Table 1.2, are consistent with Sibley et al. (2016). We find that both BWI and ASR are significantly correlated with both the value of economic indexes and growth in the indexes.

-------------- Insert Table 1.2 ---------------

Next, we investigate whether ASR captures some non-fundamental components in market sentiment. In addition to the above-mentioned literature of influences of terrorist attacks and daylight change on investor mood, solar activities are also found to be related to investor mood. Specifically, geomagnetic storms, caused by coronal mass ejections by the sun, have been found to have ubiquitous effects on mood disorders. For example, Raps et al. (1992) report significantly negative correlations between admissions of psychiatric patients and magnetic disturbance measures such as sudden magnetic disturbances of the ionosphere (–0.274) and the index of geomagnetic activity (–0.216). Kay (1994) shows a significant increase in hospital admissions with a diagnosis of depressive illness following geomagnetic storms compared to geomagnetically quiet control periods.

In Panel B we show the pairwise correlations between ASR, the number of terrorist attacks and geomagnetic activities. We obtain the number of terrorist attacks that happened on U.S. soil over 1970 to 2015 from the Global Terrorism Database produced by the National Consortium for the Study of Terrorism and Responses to Terrorism. We use two measures to proxy the intensity of geomagnetic activities, storm sudden commencement (SSC) and monthly mean of the overall strength of geomagnetic storm (GMS), both of which are downloaded from the National Geophysical Data Center and covers the time span from 1970 to 2011. If ASR captures market sentiment, we should expect sentiment to be negatively associated with the number of terrorist attacks and with geomagnetic activities. The results for ASR are as expected: it is negatively and significantly correlated with all three mood-depressing variables, that is, with the number of terrorist attacks (–0.12), with SSC (–0.13) and with GMS (–0.08).

In summary, we present evidence that ASR serves as a good candidate of market sentiment measure because it captures both fundamental and non-fundamental components affecting the market. Since we are interested in only unexpected fund flows driven by non-fundamental components, we orthogonalize ASR with a set of macroeconomic variables introduced in Baker and Wurgler (2006). After orthogonalization, the correlations between ASR and lagging, concurrent, and leading economic indexes become indistinguishable from zero. We use this orthogonalized sentiment measure in all tests throughout the paper unless otherwise specified.

1.4 Market sentiment and flow of funds

In this section we analyze the relation between change in market sentiment and mutual fund investment decisions. We first examine fund flows at the fund class level. Among the six fund classes, money market and government fixed-income funds are considered relatively safe, while equity funds are riskier. We consider the remaining three classes, hybrid, corporate fixed income, and municipal fixed income, to have intermediate risk levels. If change in market sentiment negatively correlates with risk aversion, it is reasonable to expect that investors, when they are more optimistic, pull money out of low-risk fund classes (money market funds) and move into high-risk fund class (equity funds). We further look into equity fund class and investigate the sentiment effect for aggressive growth, growth, growth and income, and income equity funds. We expect the influence of sentiment to be more prominent for aggressive growth funds than income funds.

1.4.1 Sentiment Effect on Net Flows

Table 1.3 presents our univariate analysis. We divide the entire time span, February 1984 to December 2014, into periods of either increasing or decreasing sentiment, depending on whether the current period's sentiment level is higher than the previous period's, and compare fund flows in different sentiment regimes.

Prior literature, such as Gomes and Michaelides (2005) and Peng and Xiong (2006), suggests that retail investors are risk averse and reallocate more money into safer funds when their optimism about the stock market dampens. We find consistent results in Panel A. We find greater net flows into corporate, municipal, government fixed-income funds, and money market funds during periods of decreasing sentiment, and greater net flows into equity and hybrid funds during periods of increasing sentiment. The differences in average flows between increasing and decreasing sentiment periods range from 1.2 basis points for hybrid funds to 33.1 basis points for government fixed-income funds. Though the differences in average flows for these funds are insignificant, except for government fixed-income funds, the signs are as expected. Panels B and Panel C reveal similar patterns with inflows and outflows. Equity funds experience greater inflows but smaller outflows in increasing sentiment periods, while money market funds show the opposite trend.

-------------- Insert Table 1.3 ---------------

Table 1.4 presents the regression results of net flows for each fund class. Given the magnitude of autocorrelation reported in Table 1.1, we incorporate one-, two-, and three-month lagged flows in the model[1]. Large autocorrelations are expected since a large portion of mutual fund investments are made through employer-sponsored retirement plans. According to the 2016

[1] These results remain qualitatively unchanged if we control for four lags of flows.

Investment Company Fact Book, 80 percent of mutual-fund owning households held mutual funds inside employer-sponsored plans in mid-2015. The nature of these flows are, to a large extent, independent of investor sentiment and therefore can be estimated from previous flows. Following Kamstra et al. (2017), we control for fund category return, logarithm of total net assets, capital gain overhang, return on the CRSP value-weighted market portfolios, change in consumer price index, yield on five-year treasury note, and the BEA monthly personal savings rate. All control variables are lagged by one month to avoid endogenous mutual fund investment decisions. We also include fund category fixed effect and year fixed effect to control for the heterogeneity unrelated to funds per se.

-------------- Insert Table 1.4---------------

Panel A uses net flows as a dependent variable. We find that a one percentage point increase in change in market sentiment results in an increase of 4.4 basis points in net flows into the equity funds (column 1) and a decrease of 2.6 basis points into the money market funds (column 6). The results are consistent with the preliminary findings in Table 1.3 and confirm the positive relation between optimism and risk-seeking behavior, indicating that an increase in sentiment induces investors to be less risk averse and thus to invest more into equity funds and less into money market funds. The coefficients of sentiment variable for intermediate-risk fund classes range from 0.1 to 2.0 basis points. Two explanations are possible for the loss of significance on money market funds. First, institutional investors hold a large portion of the assets in money market funds (around 40% in 2015 according to the 2016 Investment Company Fact Book), and they are less likely to be influenced by sentiment. Second, the financial assets in money market funds usually have very short maturities. The data with monthly frequency may not entirely capture the influence of market sentiment on investors in money market funds.

Panel B uses inflows as the dependent variable. We find that for a one percentage point increase in market sentiment, equity funds experience the most increase in inflows (2.9 basis points), while money market funds experience the least (negative 6 basis points). In Panel C, we find that an increase in market sentiment is associated with a significant drop in outflows of 2.4 basis points from equity funds. The effect on money market funds is negative but not significant. Overall, the results in Table 1.4 confirm our hypothesis that a change in market sentiment affects risk preferences of retail investors and their corresponding asset allocation decisions. This effect is strongest for equity funds and money market funds, while it is less pronounced for fund categories with an intermediate level of risk.

1.4.2 A Closer Examination of Domestic Equity Funds

We take a closer look at equity funds and run regressions on a sample of domestic equity funds, i.e., aggressive growth, growth, growth and income, and income funds. Since aggressive growth funds invest primarily in small and growth companies with potential for capital appreciation and income funds invest mainly in companies with good dividends, we expect that aggressive growth funds are the most sensitive to change in market sentiment and income funds are the least sensitive.

Results for domestic equity fund are given in Table 1.5. Panel A uses net flows as the dependent variable. Column 1 shows that a one-percentage-point increase in sentiment results in a significant increase of 10.1 basis points in net flows for aggressive funds. In contrast, the sentiment effect is much smaller in magnitude, though positive and significant at 1% level, for other domestic funds (column 2–4). The coefficients are 0.052, 0.025, and 0.036 for growth, growth and income, and income funds, respectively. The difference in estimated coefficients between aggressive growth and income funds is significant at 1% level ($\chi^2 = 7.07$).

-------------- Insert Table 1.5 ---------------

Panel B uses net exchanges as dependent variable. Net exchanges captures the active money transfer within a fund family and is not likely to be liquidity-driven; therefore, it represents a purer measure of varying risk aversion of individual investors. The results show a similar pattern. The sentiment-induced flows are the largest for aggressive growth funds (0.062) and smaller for other domestic equity funds (0.024, 0.009, and 0.017 for growth, growth and income, income funds, respectively). Again, the difference between aggressive growth funds and income funds is significant at 1% level ($\chi^2 = 6.70$).

A problem with testing the sentiment effect arises from the fact that the correlated mutual fund investment decisions may in reverse cause changes in market sentiment. While reverse causality might result in biased estimate of sentiment effect on net flows, it is not likely to drive our results of net exchanges. The average net exchanges is zero in percentage term and -$8.08 million in dollar value, which is small compared to average net flows ($780 million). Thus, it seems implausible to assume that net exchanges cause shifts in market sentiment.

To further address this concern, we employ an instrumental variables framework. Specifically, we repeat the tests in Table 1.5 treating shifts in sentiment as endogenous, using its lagged values as instruments. Table 1.6 reports the coefficients and standard errors on sentiment variable from second-stage IV regressions. In addition, we report the F-statistics for the test of the joint significance of instruments and the adjusted R^2s from the first-stage regression. Though the coefficients of the sentiment effect are not as sizable as the estimates in Table 1.5, the patterns and significances are largely preserved. Aggressive funds are still the most sensitive to change in market sentiment in both net flows and net exchanges regressions.

-------------- Insert Table 1.6 ---------------

1.4.3 Sentiment Effect through the Mutual Funds Flow Channel

The analyses presented so far establish that sentiment fluctuations induce unexpected flows between different mutual fund categories. A one-standard-deviation increase in market sentiment is associated with an average increase in net flows of roughly 47.5 basis points for equity funds, or approximately $14 billion, creating a buying pressure on portfolios held by mutual funds. Sentiment-induced demand could swing quickly because sentiment per se is volatile even on a weekly basis. Thus, we expect these firms to have greater trading volume and return volatility.

This prediction differs from the findings in prior literature that are based on noise trader models. They find that small, young, volatile, and non-dividend paying firms are affected by market sentiment, while bond-like stocks are less sensitive to sentiment. While prior studies investigate the influence of market sentiment on equity prices through the direct equity trading channel, we examine the role of sentiment through the mutual fund flow channel. These two channels are not mutually exclusive. In fact, we may expect the sentiment beta to be U-shaped, with “bond-like” and “lottery-like” stocks on both ends.

To test our first prediction, we build ten portfolios based solely on the sensitivity of stock returns to market sentiment and look into the average firm characteristics in each portfolio. We use our sample data from 1967 to 2014 and calculate the correlations between returns of individual stocks and market sentiment. We use 48 monthly returns to calculate the correlations. Starting in 1971, in June of every year, we rank all the stocks in the sample by correlation in ascending order. We then split the sample into deciles and form ten equally weighted portfolios, based on their correlation rankings. Although we could report results using a value-weighted scheme, we choose equally weighted portfolios for the primary reason that value-weighted returns place a heavier emphasis on the size of the stock. Also, the value-weighted measure is sensitive to within-portfolio changes in the stock price distribution (Kumar and Lee (2006)).

After the portfolios are formed, we move to the following year and calculate the monthly excess returns for each by subtracting one-month T-bill rate from portfolio returns. The top portfolio, Portfolio 10, has the highest correlation with orthogonalized market sentiment, and the bottom portfolio, Portfolio 1, has the lowest correlation. To capture more detailed dynamics, we further divide the top and bottom portfolios, Portfolios 1 and 10, into thirds, where A denotes the lowest sensitivity and C denotes highest sensitivity to market sentiment.

Table 1.7 presents the summary statistics for the ten correlation portfolios. At the end of June, we calculate the cross-sectional average of firm characteristics and report the time-series averages. A description of the variables is as follows: Market equity (ME) is measured as price times shares outstanding from CRSP. BE is the book value of stockholders' equity plus deferred taxes and the investment tax credit (if available), minus the book value of preferred stock. Book-to-market, or B/M, ratio is computed as book equity (BE) for the fiscal year ending before June divided by ME (price times shares outstanding at the end of December of year t–1). The book value of preferred stock is estimated with redemption, liquidation, or par value, depending on availability. Following Fama and French (2015) we define operating profitability as annual revenues minus the cost of goods sold, interest expense, and selling, general and administrative expenses, divided by book equity for the last fiscal year end in t–1. We define investment as the change in total assets from the fiscal year ending in year t–2 to the fiscal year ending in t–1, divided by t–2 total assets. Age is the number of years since the firm's first appearance on CRSP. The dividend payer dummy equals one if the firm has paid dividends before June of year t, and zero otherwise. A repurchaser dummy is defined in the same way as a dividend payer dummy. S&P 500 firms is defined as the average number of firms listed on the S&P 500 in each portfolio. Turnover is the monthly trading volume divided by shares outstanding.

--------------- Insert Table 1.7 ----------------

Panel A of Table 1.7 shows that Portfolio 1 has the lowest correlation, with the market sentiment variable (–0.03), while Portfolio 10 has the highest correlation (0.38). High correlation portfolios have a greater representation of large firms, profitable firms, older firms, dividend payers and repurchasers. Further, firms in these portfolios are more likely to be held by institutional investors and be included in S&P 500 index, and they have on average greater turnover rate.

Panel B of Table 1.7 reports the average monthly excess returns of the ten correlation portfolios. The returns range from 0.92% to 0.96%, and the differences are insignificant. Though we find no systemic patterns with regard to the excess returns, we do find that the standard deviation of monthly excess returns increases across the ten portfolios. This evidence is consistent with our expectation that portfolios with higher sensitivity to market sentiment suffer more price deviation.

We further use the orthogonalized sentiment index to classify the entire time span into increasing (decreasing) sentiment periods if the sentiment level is higher (lower) than the previous month. Of all 522 monthly observations, 260 are classified as increasing sentiment periods and 262 as decreasing sentiment periods. Their distribution is almost even in the sample. Panel B of Table 1.7 reveals a strong variation in average returns across the ten portfolios. In periods of increasing sentiment, the monthly excess returns increase almost monotonically with sensitivity to market sentiment. The excess returns range from 2.76% for Portfolio 1 to 3.28% for Portfolio 10. In periods of decreasing sentiment, we find an opposite trend that the portfolios' excess returns exhibit a monotonically decreasing pattern with sensitivity. For instance, Portfolio 1 has a monthly excess return of –0.89%, while Portfolio 10 only –1.34%. Our untabulated results for extreme portfolios show an even larger spread. Portfolios 10C that contains the top one third of highest-sensitivity stocks outperforms (underperforms) Portfolio 1A that contains the bottom one third of lowest-sensitivity stocks by 90 (67) basis points in increasing (decreasing) sentiment periods. These patterns suggest a predictable relationship between portfolio excess returns based on correlation with market sentiment.

These results are consistent with the prediction that firms favored by mutual funds are notably vulnerable to market sentiment. From the firm characteristics side, the high proportion of large companies with large institutional holdings in high-correlation portfolios suggests that sensitivity to sentiment is indeed related to the demand created from the mutual fund industry. From the return side, these firms seem to be more volatile than firms in low-correlation portfolios.

1.5 Market Sentiment and Cross-Sectional Stock Returns

In this section we explore the possibility of using market sentiment as a factor in explaining stock returns. Specifically, we construct the sentiment factor following Carhart (1997) and test whether this factor helps to explain cross-sectional stock returns.

1.5.1 Construction of the Market Sentiment Factor

We follow the Carhart (1997) method in building a momentum factor to construct our market sentiment factor, SENT. We sort firms on correlation with sentiment into three portfolios using breakpoints of 30% and 70%. For each month, we define SENT as the difference in equal-weighted portfolio excess returns between the top and bottom portfolios. Table 1.8 reports average monthly returns and pairwise correlation for the factor portfolios: MRP, SMB, HML, MOM, RMW, CMA and SENT. Column (1) in Panel A reports the monthly excess returns. In line with previous asset pricing research, excess returns of all factors except SENT are positive, with high variances. This is indicative of the considerable cross-sectional variation in portfolio excess returns that these variables can explain. Although the correlations among factors are significant, they are generally low except for the pair of HML and CMA. The correlation between them is 0.70 and is significant at 0.1%. The evidence supports Fama and French (2015), in which the authors point out that HML is a redundant factor.

-------------- Insert Table 1.8 ---------------

The average monthly return on the SENT factor is 0.02 and not significantly different from zero (t-statistic = 0.18). Considering the patterns found in the sensitivity portfolios in the previous section, this can be explained by offsetting the positive returns in periods of increasing sentiment with negative returns in periods of decreasing sentiment. Panels B and C report the summary of the risk-mimicking portfolios in increasing- and decreasing-sentiment periods separately, and confirm our inference on the low excess returns on the SENT factor for the entire sample. The SENT factor is positive (0.39) and significantly different from zero (t-statistic = 2.72) during periods of increasing sentiment and negative (–0.35) and significantly different from zero during periods of decreasing sentiment (t-statistic = –3.42). Even though the average premium on SENT is close to zero, it doesn't necessarily mean that the SENT factor does not help to explain asset prices. On the contrary, the results indicate that SENT captures a short-term deviation from the fundamental values that results from sentiment-induced price pressure from mutual fund flows. These deviations are nulled out over periods of increasing and decreasing sentiment. For illustration, Figure 1 shows monthly averages by year of SENT in comparison with monthly averages of other asset pricing factors: MRP, SMB and HML. SENT fluctuates with similar magnitudes as other factors, especially since late 1990s, the period of large growth in mutual fund industry[2].

------------- Insert Figure 1 -------------

We also find that regardless of increasing or decreasing sentiment, the excess return on the market (MRP) always plays a major role in asset pricing, consistent with the current body of literature. Like SENT, SMB shows opposite signs over increasing and decreasing sentiment periods. The excess returns on HML, RMW and CMA show that they contribute almost nothing in time of increasing sentiment but contribute tremendously in time of decreasing sentiment. This finding is consistent with Baker and Wurgler (2006). They argue that risks are not correctly priced when sentiment is high. MOM shows a much stronger effect in periods of decreasing sentiment than in periods of increasing sentiment. In contrast, the monthly returns on SENT are significant both statistically and economically across both sentiment regimes.

1.5.2 Are Investors Compensated for Bearing Sentiment Risk?

In the last section we showed that on average the risk premium associated with sentiment risk factor, SENT, is not significantly different from zero. One might conclude that sentiment is not priced and hence carries no importance in asset pricing. The question "Is sentiment risk priced?" can be effectively broken down into two separate questions: (1) "Does market sentiment affect asset prices?" and (2) "Are investors compensated for bearing sentiment risk?" This paper aims to answer the first question and our answer is "yes". As we present earlier and will show in the following sections, SENT captures short-term mispricing that results from sentiment-induced

[2] We also construct the SENT factor in different fashions, the results are qualitatively unchanged (unreported results). For example, we form value-weighted portfolios instead of equal-weighted ones; we use NYSE stock breakpoints; we follow Fama and French (1993) and build six value-weighted portfolios on size and correlation, etc.

mutual fund flows. It significantly explains returns of correlation portfolios and portfolios formed on size, book-to-market ratio, operating profitability, investment, and institutional ownership.

For the second question, however, the zero risk premium on SENT seems to suggest that in the long run investors are not compensated for bearing sentiment risk. In fact, this is consistent with two strands of existing literature, the noise trader hypothesis and flow-based temporary price pressure hypothesis.

The role of noise traders in asset pricing is first formalized in De Long et al. (1990). The noise trader model hinges on two crucial assumptions. First is that change in sentiment leads to noise trading. Second is that arbitrageurs are risk-averse and have short horizons. As a result, arbitrageurs in fear of the unpredictability of noise traders' sentiment limit their original arbitrage position. De Long et al. (1990) also point out that as horizons of sophisticated investors increase, they trade more aggressively and push the price of risky asset closer to their fundamental values. In this case, even though the sentiment risk created by noise traders is not priced, it still creates extra volatility in asset prices. Our findings in Panel B, Table 1.7 are consistent with this argument. We show that though returns on correlation portfolios have no trend, the volatility of returns increases monotonically with sensitivity to market sentiment. Similarly, Sias, Starks and Tiniç (2001) show that returns on closed-end fund shares are more volatile than the returns on the underlying assets, but fund's shareholders do not earn returns greater than holders of the underlying assets. They argue accordingly that closed-end fund shareholders are not compensated for bearing sentiment risk created by noise traders.

Our results are also consistent with the flow-based temporary price pressure literature. Several recent studies have shown that the flow-induced trading creates temporary price impact that is reversed in subsequent quarters. For example, Coval and Stafford (2007) show inflow-driven purchases result in persistent institutional price pressure, which lasts around two quarters and takes more quarters to reverse. Ben-Rephael et al. (2011)); Ben-Rephael et al. (2012) show that fund flows are positively correlated with market returns, and that 85% (all) of the positive relation between the net exchanges of equity funds and aggregate stock market excess returns is reversed within four (ten) months. Lou (2012) find that flow-induced trading positively forecasts stock and mutual fund returns in the following year, which are then reversed in subsequent years.

Since the sentiment-induced temporary pressure is not based on fundamental information that directly affects future earnings, but rather on non-fundamental signals, it should not affect equilibrium prices in the long run. In the short run, however, the effect could be substantial. This explains why we only find economic significance of SENT at the monthly frequency or in an annual window.

1.5.3 The Sentiment Factor in Asset Pricing

Next, we assess the pricing abilities of the sentiment factor, SENT, alongside of other time-varying risk factors. We also report evidence comparing the asset pricing model with SENT as an additional risk factor to other standard asset pricing models. The baseline model examined in this section consists of six risk factors: the first five factors are factors used in Fama and French (2015) and the sixth is the momentum factor proposed in Jegadeesh and Titman (1993) and Carhart (1997). To test the incremental explanatory power of SENT, we augment the baseline model with the sentiment factor (SENT). Specifically, our factor model for portfolio p is as follows:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{1,p}MRP_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}RMW_t + \beta_{5,p}CMA_t + \beta_{6,p}MOM_t + \beta_{7,p}SENT_t + \varepsilon_{p,t}. \quad (3)$$

We conduct tests on the ten portfolios formed on correlation with market sentiment over the entire sample period, as well as during periods of increasing and decreasing sentiment. Table

1.9 reports the estimates of sentiment-augmented factor model for each of the correlation-portfolios as well as the extreme portfolios[3]. We find that the SENT factor loadings are significant at a 1% level across all portfolios except for Portfolio 7, which has the intermediate level of sensitivity to market sentiment. Consistent with our hypothesis, the low-sensitivity portfolios (Portfolio 1 – 3) have negative SENT loadings, while the high-sensitivity portfolios (Portfolio 8 – 10) have positive loadings. In addition, we observe large improvements in adjusted R^2s in the sentiment-augmented model from the baseline model, especially for the low-sensitivity portfolios. For instance, the adjusted R^2s increase by approximately 10% from 82.4% (74.4%) to 92% (86%) for Portfolio 1 (Portfolio 1A).

------------- Insert Table 1.9 -------------

In untabulated results for the baseline six-factor model, we see that the loading on MRP increases monotonically with the sensitivity to market sentiment, while the loadings on HML and MOM show a decreasing pattern. However, after we add the SENT factor, all patterns vanish. The coefficients of MRP are now close to one in the SENT-augmented model, as opposed to the baseline model in which the coefficients range from 0.81 for Portfolio 1A to 1.07 for Portfolio 10C. The loadings on SENT increase monotonically from –0.93 (–1.01) for Portfolio 1 (Portfolio 1A) and 0.41 (0.50) for Portfolio 10 (Portfolio 10C). It appears that only SENT shows this monotonic variation across portfolios that could explain the differences in excess returns. Additionally, in explaining the spreads between Portfolios 1 and 10, and between Portfolios 1A and 10C, we find that SMB, HML, RMA, CMA, and MOM lose most of their explanatory powers after we include SENT into the model, and that SENT is the only variable that remains significant in explaining the spreads. The Adj-R^2s improve from 18.5% to 86% and from 20.2% to 67.5% for

[3] For simplicity, we report only the results of SENT-augmented models for the entire time span.

the spreads 10–1 and 10C–1A respectively, further demonstrating the incremental power of SENT in explaining the cross-section of returns.

We also perform the same test over sub-periods, namely increasing- and decreasing-sentiment periods in untabulated analysis. For both sub-periods, we find similar results to our findings in Table 1.9. The SENT factor created from the market sentiment continues to be significant at the 1% level across all portfolios, except for Portfolios 6 and 7. Also, the Adj-R^2s of the sentiment-augmented models show significant improvements from the four-factor model, consistent with our findings from Table 1.9. Similarly, the improvements weaken as the correlation of returns with market sentiment increases. In explaining the spreads between Portfolios 1 and 10, and between Portfolios 1A and 10C, other factors lose at least part of their explanatory power after addition of the SENT factor.

We show in Table 1.8 significant correlations between SENT and all other risk factors. The results in Table 1.9 consistently show that the addition of SENT absorbs part of the explanatory power of other risk factors. Taken together, these findings suggest that the explanatory power of SENT lies not only in improving Adj-R^2s across different model settings, but also in its interaction with other risk factors. Though it is beyond the scope of this study, our results speak to a possibility of SENT being able to explain some long-lasting anomalies, for example, the value anomaly and the momentum anomaly.

1.5.4 Robustness Tests

The results documented so far suggest that the SENT factor has significant explanatory power in the cross-section of portfolio returns. Further prescription for using the SENT factor is conditional on whether the findings persist in a series of robustness checks. It is beyond the scope of this study to augment all available asset pricing models with the SENT factor. However, we examine the explanatory power of SENT in two other important asset pricing models: the Fama-French three-factor model and the more recent Fama-French five-factor model.

Table 1.10 reports the SENT loadings in sentiment-augmented three-, four-, and five-factor models. Columns (1) and (3) show the incremental explanatory power of SENT in the Fama-French three-factor model and five-factor model. Fama and French (2015) show evidence that the value premium factor, HML, does not improve the explanatory power of the cross-section of returns in their five-factor model because of its redundancy. They argue that dropping HML from the five-factor model to create a new four-factor model that captures market, size, profitability, and investment premiums retains the explanatory power of the value premium because HML appears to be a redundant factor, at least for US stock return data from 1963 to 2013. We omit HML in column (2) to verify the robustness of our results by augmenting the SENT factor in their new model.

--------------- Insert Table 1.10 ---------------

If returns were completely unrelated to the market sentiment factor, after controlling for the market risk premium, size, and value premium, then the loadings across the portfolios would not capture any variation. For the most part, our findings suggest that market sentiment has significant explanatory power in asset pricing. In the regressions shown in Tables 1.9, the significance of SENT persists across almost all portfolios, despite including the profitability and investment factors in the traditional FF three-factor model. In untabulated regression results of the benchmark models, we find improvements in Adj-R^2s that are consistent with our earlier findings. In addition, SENT reduces the explanatory power of RMW and CMA, especially for high-sensitivity portfolios in terms of significance and magnitude. In sum, the findings from Table 1.10

suggest that the addition of market sentiment as an explanatory factor in pricing asset returns is persistent across frequently used asset pricing models.

Previous tests were carried out on portfolios formed according to their correlations with market sentiment. To ensure that these findings are not merely artifacts of our sorting procedure or our sample, we examine the pricing power of SENT on portfolios sorted by other firm characteristics. We obtain portfolios based on size, book-to-market ratio, operating profitability, and investment from the Kenneth R. French data library from 1971 to 2014. We also sort firms by institutional holdings using our sample over 1980 to 2014[4]. We report SENT loadings in Table 1.11 for these portfolios.

--------------- Insert Table 1.11 ---------------

Our hypothesis predicts that stocks favored by mutual funds are more vulnerable to market sentiment due the sentiment-induced temporary price pressure. Therefore, we should be able to find a trend in the SENT loadings if we sort portfolios based on firm characteristics reflecting the taste of institutions. Table 1.11 show supportive evidence. Column (1) reports the SENT loadings for size portfolios. We find that the SENT loading is positive and significant for most of the large-cap stock portfolios but negative and significant for the portfolio of the smallest size decile. Column (2), (3) and (4) show that low B/M portfolios, high operating profitability portfolios, and high investment portfolios have significantly more loadings on SENT. This is consistent with findings in the previous literature that mutual funds tend to hold past winners and sell past losers, where past winners are more likely to have low B/M and high operating profitability, and are more inclined to increase their capital investments (See Titman, Wei and Xie (2004)). Column (5) reports the loadings for portfolios sorted on institutional holdings. We see a monotonic increasing

[4] Shorter time period is due to data availability for institutional holdings.

pattern in SENT loadings as institutional holdings increase. Portfolios with high institutional ownership (Portfolio 9 and 10) exhibit positive SENT loadings, while other portfolios with lower institutional ownership show negative and significant loadings. Further, in explaining the return spreads between the top and bottom portfolios, SENT shows significance at the 1% level in regressions of size, book-to-market, operating profitability, investment and institutional ownership portfolios.

1.6 Conclusion

This study investigates a crucial yet underreported channel, mutual fund flows, through which market sentiment affects asset prices. We find that following an increase in market sentiment, investors increase their investments in riskier fund categories and reduce their investments in safer funds. Specifically, increases in market sentiment are positively associated with net flows into equity funds but negatively associated with net flows into money market funds. Further, among domestic equity fund categories, we find that aggressive growth funds are the most sensitive to this sentiment effect, while other funds, i.e., growth, growth and income, and income funds, are modestly affected.

We propose a sentiment-induced price pressure hypothesis based on the association established between market sentiment and mutual fund flows. This hypothesis predicts that stocks favored by mutual funds are vulnerable to market sentiment. Consistently, we show that portfolios highly correlated with sentiment generally have greater representation of large-cap stocks, dividend payers, repurchasers, firms with high institutional holdings, and those included in the S&P 500 index. We follow Carhart (1997) and construct a sentiment factor. The addition of a sentiment factor increases the factor models' explanatory powers and reduces the explanatory powers of other risk factors, including book-to-market, operating profitability, investment, and momentum factors. Finally, we show that the significance of SENT persists across different model settings and is robust to a variety of sorting procedures. Consistent with our prediction, we find the SENT loadings are positive and significant for large-cap stock portfolios and high institutional ownership portfolios, while the loadings are negative for small-cap and low institutional ownership portfolios.

Although the SENT factor is significant in all asset pricing models, it has an average risk premium not significantly different from zero. This finding suggests that SENT captures mostly short-term mispricing. In the long run, asset prices still converge to the fundamentals, implying sentiment risk does not create long-lasting market inefficiency.

We emphasize the importance of analyzing mutual fund flows to understand the role of market sentiment in asset pricing. Our results run counter to prior studies. While existing literature infers the role of market sentiment in asset pricing through the direct equity trading channel, we examine the mutual fund flow channel. Though the predictions from these two channels are largely different, they are not mutually exclusive. We consider the mutual fund flows channel to be of greater economic importance because 1) the majority of individual investors own equity assets indirectly through their shares in funds; and 2) stocks affected through the direct trading channel are mainly small-cap and constitute only less than 20% of total market capitalization.

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Table 1.1
Summary Statistics

Panel A reports summary statistics of aggregate fund flows and macroeconomic control variables from February 1984 to December 2014. The fund return is the capital appreciation for that asset class. Assets are the total net assets in billions. Capital gain is the cumulative returns since the previous November. Personal saving is the monthly BEA personal saving rate. CPI is the change in consumer price index. Market return is the return on a value-weighted market portfolio from CRSP. Five-year Treasury is the annualized return on a five-year Treasury note. Panel B describes the net flows in detail for each asset class. Panel C describes the measure of market sentiment.

Panel A: Summary statistics

	Mean	Median	Standard Deviation	Min	Max
Net flows (%)	0.94	0.61	2.20	–5.97	15.13
Net Exchanges (%)	0.00	-0.01	0.49	-2.11	3.46
Fund return (%)	1.15	1.10	3.09	–23.42	21.74
Assets (in billions)	985.81	405.82	1430.99	8.70	8440.92
Capital gains (%)	9.13	5.93	15.07	–43.13	171.70
Personal saving (%)	6.13	5.95	1.97	1.90	11.20
CPI (%)	0.23	0.23	0.26	–1.77	1.38
Market return (%)	0.96	1.47	4.47	–22.54	12.85
Five-year Treasury (%)	5.02	5.03	2.63	0.62	13.48

Panel B: Flow of funds into different asset classes

	N	Mean %	Median %	Standard Deviation, %	Partial Autocorrelation			
					Lag 1	Lag 2	Lag 3	Lag 4
Equity	371	0.58	0.46	0.85	0.571	0.270	0.209	0.087
Hybrid	371	0.97	0.69	1.27	0.776	0.276	0.352	–0.062
Corporate bonds	371	1.25	1.16	1.21	0.767	0.164	0.217	0.013
Municipal bonds	371	0.85	0.63	1.45	0.790	0.238	0.159	0.136
Government bonds	371	0.83	0.42	2.54	0.518	0.361	0.211	0.266
Money market	371	0.64	0.46	2.25	0.149	0.074	0.404	–0.137

Panel C: Descriptive statistics of market sentiment

	Min	25%	Median	Mean	75%	Max	Std. deviation
Sentiment	32.01	52.85	61.40	60.38	68.75	84.88	10.55

Table 1.2
Comparison of Sentiment Indexes

This table reports the comparison between the orthogonalized Baker and Wurgler (2006) sentiment index (BWI) and the Advisors' Sentiment Report (ASR) from the Investors Intelligence. Panel A reports the pairwise correlations between sentiment measures and economic indexes and growth in the indexes. We obtain monthly lagging (Lag), coincident (Coin), and leading (Lead) economic indexes from the Conference Board over 1970 to 2015. gLag, gCoin, and gLead denote the growth over t–12 value respectively. Panel B reports the correlations between sentiment indexes and terrorist attacks and geomagnetic activities. NTerror is the number of terrorist attacks obtained from Global Terrorism Database produced by the National Consortium for the Study of Terrorism and Responses to Terrorism. SSC and GMS denote the number of storm sudden commencement and monthly mean of the overall strength of geomagnetic storms, respectively. *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

Panel A: Economic indexes

	ASR	BWI	Lag	Coin	Lead	dLag	dCoin	dLead
ASR	1.00							
BWI	–0.19***	1.00						
Lag	0.25***	0.18***	1.00					
Coin	0.25***	0.20***	0.99***	1.00				
Lead	0.26***	0.20***	0.93***	0.97***	1.00			
gLag	–0.14***	0.17***	0.24***	0.24***	0.32***	1.00		
gCoin	0.08*	0.13***	–0.03	0.04	0.21***	0.44***	1.00	
gLead	0.30***	0.01	–0.03	0.01	0.15***	–0.01	0.77***	1.00

Panel B: Non-fundamental components in sentiment

	ASR	BWI	NTerror	SSC	GMS
ASR	1.00				
BWI	–0.19***	1.00			
NTerror	–0.12***	–0.02	1.00		
SSC	–0.13***	0.13***	0.04	1.00	
GMS	–0.08*	–0.03	0.03	0.40***	1.00

Table 1.3
Flow of Funds Under Different Sentiment Regimes

This table reports the average fund flows in two sentiment regimes: increasing and decreasing sentiment months over the period from February 1984 to December 2014. A month is in an increasing sentiment period if the sentiment level in the current month is higher than that in the previous month. The difference in average flows between two different sentiment regimes and the significance of the difference is also given.

	High risk	Medium risk				Low risk
	Equity	Hybrid	Corporate bond	Municipal bond	Government bond	Money market
Panel A: Net flows						
Increasing	0.947	1.005	1.353	0.919	0.739	0.627
Decreasing	0.802	0.993	1.418	1.046	1.070	0.771
Inc–Dec	0.145	0.012	–0.065	–0.128	–0.331	–0.145
t-statistic	1.541	0.126	0.407	–1.223	–2.156	–0.611
Panel B: Inflows						
Increasing	4.390	2.911	4.618	3.478	12.094	45.210
Decreasing	4.328	2.941	4.832	3.642	12.620	45.422
Inc–Dec	0.062	–0.030	–0.214	–0.163	–0.526	–0.211
t-statistic	0.473	–0.332	–1.349	–1.491	–0.985	–0.227
Panel C: Outflows						
Increasing	3.443	1.906	3.265	2.559	11.355	44.584
Decreasing	3.526	1.948	3.414	2.595	11.550	44.650
Inc–Dec	–0.084	–0.042	–0.149	–0.036	–0.195	–0.067
t-statistic	–0.881	–1.070	–2.247	–0.558	–0.377	–0.075

Table 1.4
Aggregate Fund Flows and Change in Sentiment

This table reports baseline regression results of aggregate flows on the change in market sentiment. The dependent variables in Panels A, B, and C are net flows, inflows, and outflows, respectively. Fund flows are scaled with lagged total net assets. ΔSentiment is the change in the market sentiment proxied by Advisor Sentiment Report (ASR). We include lagged dependent variables to control for autocorrelation. Fund return is the capital appreciation for month t and asset class i. Assets are the logarithm of total net assets. Capital gain is cumulative realized return since the previous November. Market return is the monthly return on the CRSP value-weighted market portfolio, including all distributions. CPI is the change in the consumer price index. Treasury is the annualized yield on a five-year treasury note. Personal saving is the BEA monthly personal savings rate. All control variables are lagged by one period. We control for fund category fixed effects and year effects in each regression. Robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	High risk	Medium risk				Low risk
	Equity	Hybrid	Corporate bond	Municipal bond	Government bond	Money market
	Panel A: Net flows					
ΔSentiment	0.044***	0.019***	0.020*	0.012*	0.001	-0.026
	(0.007)	(0.005)	(0.011)	(0.007)	(0.011)	(0.025)
Flow_{t-1}	0.432***	0.335***	0.185**	0.290***	0.092*	-0.168
	(0.068)	(0.079)	(0.091)	(0.091)	(0.048)	(0.166)
Flow_{t-2}	0.061	0.091*	0.122**	0.154***	0.144***	-0.090*
	(0.083)	(0.050)	(0.060)	(0.054)	(0.038)	(0.047)
Flow_{t-3}	-0.017	0.214**	0.048	0.131**	0.167***	0.172**
	(0.058)	(0.087)	(0.066)	(0.056)	(0.062)	(0.070)
Fund return_{t-1}	0.014**	0.054	-0.012	0.025*	0.055*	0.157
	(0.006)	(0.035)	(0.014)	(0.014)	(0.028)	(0.162)
Assets_{t-1}	-0.249	-0.125	-0.548	-0.347***	-0.564***	-2.055***
	(0.250)	(0.101)	(0.357)	(0.115)	(0.190)	(0.631)
$\text{Capital gain}_{t-1}$	-0.001	-0.003	0.005	0.001	0.009**	0.056*
	(0.001)	(0.004)	(0.010)	(0.005)	(0.005)	(0.029)
$\text{Market return}_{t-1}$	-0.053***	-0.017	-0.007	-0.012	0.001	0.020
	(0.014)	(0.020)	(0.023)	(0.011)	(0.021)	(0.029)
CPI_{t-1}	-0.011	-0.136	0.165	0.070	0.009	-0.918
	(0.098)	(0.113)	(0.175)	(0.145)	(0.200)	(0.631)
Treasury_{t-1}	-0.047	-0.328***	-0.085	0.144*	0.190	0.041
	(0.088)	(0.084)	(0.210)	(0.085)	(0.155)	(0.215)
$\text{Personal saving}_{t-1}$	0.031	0.086**	0.125**	0.064	0.063	-0.109
	(0.052)	(0.035)	(0.061)	(0.053)	(0.081)	(0.197)
Constant	2.650	3.971***	3.619	1.425	4.706*	25.368***
	(2.356)	(1.212)	(4.484)	(1.634)	(2.589)	(7.389)
Fund category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3158	1400	2656	1328	2064	736
Adjusted R^2	0.438	0.599	0.207	0.594	0.452	0.143

Table 1.4 – continued

	High risk	Medium risk				Low risk
	Equity	Hybrid	Corporate bond	Municipal bond	Government bond	Money market
			Panel B: Inflows			
ΔSentiment	0.029***	0.009*	-0.002	0.004	-0.009	-0.060
$Flow_{t-1}$	0.502***	0.342***	0.197**	0.264**	0.481***	0.249***
$Flow_{t-2}$	0.112	0.087*	0.153**	0.222**	0.062	0.080**
$Flow_{t-3}$	0.051	0.227***	0.086	0.199**	0.301***	0.232***
Fund $return_{t-1}$	-0.004	0.033	-0.021	0.012	-0.151***	-0.023
$Assets_{t-1}$	-0.421*	-0.008	-0.569	-0.273***	-0.248	-0.644
Capital $gain_{t-1}$	-0.002**	-0.005	-0.002	-0.003	-0.001	-0.062
Market $return_{t-1}$	-0.026**	-0.008	-0.023	-0.006	0.039*	0.116**
CPI_{t-1}	-0.103	-0.311**	-0.045	-0.168	-0.306	-0.654
$Treasury_{t-1}$	-0.247**	-0.324***	-0.292	0.036	0.135	0.504
Personal $saving_{t-1}$	0.044	0.054	0.089	0.016	-0.082	-0.470
Constant	7.687***	4.369***	7.859*	3.437**	3.407	21.002
Fund category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3158	1400	2656	1328	2064	736
Adjusted R^2	0.678	0.577	0.246	0.728	0.940	0.815
			Panel C: Outflows			
ΔSentiment	-0.024***	-0.010***	-0.023***	-0.010**	-0.011	-0.021
$Flow_{t-1}$	0.406***	0.345***	0.385***	0.316***	0.391***	0.187***
$Flow_{t-2}$	0.246***	0.146***	0.157***	0.036	-0.068**	0.065*
$Flow_{t-3}$	0.162***	0.191***	0.157***	0.120***	0.456***	0.396***
Fund $return_{t-1}$	-0.010**	-0.020***	-0.001	-0.015***	0.051***	0.206***
$Assets_{t-1}$	-0.279	0.110***	-0.019	0.096	0.388**	1.273
Capital $gain_{t-1}$	-0.002**	-0.002**	-0.002**	-0.001	-0.006***	-0.091***
Market $return_{t-1}$	0.028***	0.009**	-0.009	0.006	0.033**	0.101***
CPI_{t-1}	-0.062	-0.157***	-0.054	-0.269**	-0.189	0.443
$Treasury_{t-1}$	-0.211***	0.002	-0.252***	-0.076	-0.072	0.404
Personal $saving_{t-1}$	-0.010	-0.031*	-0.024	-0.029	-0.104	-0.329
Constant	-0.024***	-0.010***	-0.023***	-0.010**	-0.011	-0.021
Fund category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3158	1400	2656	1328	2064	736
Adjusted R^2	0.735	0.542	0.562	0.568	0.960	0.887

Table 1.5
Equity Fund Flows and Change in Sentiment

This table presents the regression results for domestic equity funds. The dependent variables used in Panels A and B are net flows and net exchanges, respectively. Fund flows are scaled with lagged total net assets. ΔSentiment is the change in the market sentiment proxied by Advisor Sentiment Report (ASR). Control variables are described as in Table 4. Robust Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Aggressive Growth	Growth	Growth and Income	Income
	Panel A: Net flows			
ΔSentiment	0.101***	0.052***	0.025***	0.036***
	(0.024)	(0.009)	(0.005)	(0.008)
$Flow_{t-1}$	0.148	0.370***	0.414***	0.350***
	(0.117)	(0.082)	(0.069)	(0.080)
$Flow_{t-2}$	0.222**	0.192***	0.121**	0.200***
	(0.098)	(0.068)	(0.060)	(0.065)
$Flow_{t-3}$	0.215**	0.214***	0.267***	0.211***
	(0.087)	(0.071)	(0.057)	(0.052)
Fund $return_{t-1}$	0.073***	0.005	0.004	0.067***
	(0.027)	(0.027)	(0.010)	(0.022)
$Assets_{t-1}$	-0.198	-0.135	-0.124*	-0.271***
	(0.235)	(0.082)	(0.064)	(0.098)
Capital $gain_{t-1}$	-0.002	0.001	-0.000	-0.001
	(0.005)	(0.003)	(0.002)	(0.004)
Market $return_{t-1}$	-0.140***	-0.046	-0.016	-0.075***
	(0.036)	(0.029)	(0.011)	(0.020)
CPI_{t-1}	-0.003	0.023	-0.158*	-0.041
	(0.210)	(0.107)	(0.090)	(0.123)
$Treasury_{t-1}$	-0.015	-0.035	-0.029	-0.055**
	(0.097)	(0.035)	(0.022)	(0.024)
Personal $saving_{t-1}$	-0.044	-0.035	-0.013	-0.014
	(0.101)	(0.037)	(0.027)	(0.046)
Constant	3.032	2.249	1.992*	3.504**
	(3.890)	(1.420)	(1.075)	(1.365)
N	368	368	368	368
Adjusted R^2	0.322	0.467	0.592	0.716

Table 1.5– Continued

Equity Fund Flows and Change in Sentiment Regimes

	Aggressive Growth	Growth	Growth and Income	Income
	Panel B: Net exchanges			
ΔSentiment	0.062***	0.024***	0.009***	0.017***
	(0.017)	(0.005)	(0.002)	(0.004)
$Flow_{t-1}$	-0.144*	-0.136*	0.255***	0.175*
	(0.080)	(0.069)	(0.079)	(0.105)
$Flow_{t-2}$	-0.035	-0.053	-0.015	0.140**
	(0.087)	(0.071)	(0.103)	(0.060)
$Flow_{t-3}$	0.079	0.071	0.141	0.054
	(0.085)	(0.093)	(0.093)	(0.052)
Fund $return_{t-1}$	0.054***	0.017	0.003	0.037**
	(0.021)	(0.017)	(0.005)	(0.015)
$Assets_{t-1}$	0.288*	0.112**	0.002	-0.011
	(0.156)	(0.047)	(0.031)	(0.049)
Capital $gain_{t-1}$	-0.002	0.002	0.001*	0.000
	(0.003)	(0.002)	(0.001)	(0.002)
Market $return_{t-1}$	-0.093***	-0.027	-0.007	-0.043***
	(0.028)	(0.018)	(0.005)	(0.012)
CPI_{t-1}	0.213	0.094*	-0.010	0.015
	(0.133)	(0.053)	(0.028)	(0.067)
$Treasury_{t-1}$	0.075	0.033*	-0.012	-0.027**
	(0.057)	(0.018)	(0.010)	(0.011)
Personal $saving_{t-1}$	0.077	0.035*	0.005	0.014
	(0.063)	(0.021)	(0.012)	(0.030)
Constant	-4.438*	-1.928**	-0.029	0.142
	(2.545)	(0.812)	(0.518)	(0.686)
N	368	368	368	368
Adjusted R^2	0.168	0.142	0.165	0.252

Table 1.6
Equity Fund Flows and Change in Sentiment: 2SLS Estimation

In this table we repeat the tests in Table 5 with instrumental variables. We use one-, two-, three-, and four-month lagged values of ΔSentiment as instruments for ΔSentiment. The dependent variables used in Panels A and B are net flows and net exchanges, respectively. Fund flows are scaled with lagged total net assets. ΔSentiment is the change in the market sentiment proxied by Advisor Sentiment Report (ASR). Control variables are described as in Table 4. Robust Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Aggressive Growth	Growth	Growth and Income	Income
		Panel A: Net flows		
ΔSentiment (instrumented)	0.100***	0.045***	0.005	0.026
	(0.033)	(0.017)	(0.014)	(0.017)
Control for lagged flows	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
N	367	367	367	367
Adjusted R^2	0.323	0.468	0.578	0.715
1^{st} Stage F-statistic	15.086	13.766	13.555	15.339
1^{st} Stage Adjusted R^2	0.318	0.323	0.324	0.333
		Panel B: Net exchanges		
ΔSentiment (instrumented)	0.040**	0.014**	0.011*	0.028***
	(0.017)	(0.007)	(0.006)	(0.008)
Control for lagged flows	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
N	367	367	367	367
Adjusted R^2	0.151	0.123	0.160	0.227
1^{st} Stage F-statistic	17.443	15.299	14.189	18.239
1^{st} Stage Adjusted R^2	0.324	0.325	0.32	0.329

Table 1.7
Summary Statistics of Portfolios Formed on Correlations with Market Sentiment: July 1971 to December 2014

Panel A reports the summary statistics of ten correlation portfolios. ρ is the correlation between return and orthogonalized market sentiment. ME and BE are market equity and book equity, respectively. B/M ratio is computed as book equity (BE) for the fiscal year ending before June divided by ME at the end of December of year t -1. Operating profitability is the annual revenues minus the cost of goods sold, interest expense, selling, general and administrative expenses divided by book equity for the last fiscal year end in t–1. Investment is the change in total assets from the fiscal year ending in year t–2 to the fiscal year ending in t–1 divided by t–2 total assets. Dividend payer dummy equals to one if a firm has paid dividends before June of year t. Repurchasers are defined in the same way as dividend payer. Inst holdings are institutional holdings from Thomson Reuters. SP500 firms is the average percentage of firms listed in the S&P 500 in each portfolio. Turnover is the monthly trading volume divided by shares outstanding. Panel B report the time-series average of correlations and excess returns of the monthly portfolios. We use the orthogonalized Advisor Sentiment Report (ASR) index to classify the whole time span into increasing sentiment periods (decreasing sentiment periods) if the sentiment level is higher (lower) than previous month.

	1 (low)	2	3	4	5	6	7	8	9	10 (high)
Panel A: summaries statistics of portfolios formed on correlations with market sentiment										
ρ	-0.03	0.07	0.12	0.15	0.18	0.21	0.24	0.28	0.32	0.38
ME	1646	1638	1659	1774	1882	1740	1907	2020	1813	1974
BE	778	682	730	762	787	795	912	886	812	936
B/M	0.77	0.59	0.75	0.74	0.78	0.76	0.76	0.78	0.78	0.76
Operating Profitability	0.17	0.20	0.15	0.24	0.24	0.09	0.27	0.27	0.18	0.40
Investment	0.18	0.14	0.13	0.14	0.13	0.13	0.14	0.12	0.15	0.14
Age	15.97	16.10	16.74	16.98	17.08	17.63	17.74	18.05	18.16	18.65
Div payers (%)	57.34	57.86	58.78	59.25	58.87	59.53	59.84	59.85	58.97	59.65
Repurchasers (%)	45.05	47.57	48.69	50.17	50.11	51.33	53.90	54.47	54.75	55.75
Inst holdings (%)	33.40	35.74	37.08	37.24	38.47	39.76	40.56	41.55	42.75	46.41
SP500 firms (%)	7.48	8.62	9.79	10.06	10.34	11.45	12.31	12.92	12.58	14.16
Turnover (%)	9.07	9.82	9.49	9.35	9.34	9.53	9.33	9.42	9.53	10.26
Panel B: excess returns on portfolios formed on correlations with market sentiment										
Return	0.92	0.93	0.97	0.92	0.91	0.92	0.94	0.98	0.93	0.96
Std. Dev	5.43	5.65	5.53	5.79	5.76	5.83	5.77	5.91	6.05	6.12
Return (increasing)	2.76	2.83	2.93	2.94	3.01	3.06	3.04	3.20	3.19	3.28
Return (decreasing)	-0.89	-0.95	-0.97	-1.08	-1.18	-1.21	-1.15	-1.21	-1.32	-1.34

Table 1.8
Summary Statistics of Risk Factor-mimicking Portfolios

Panel A reports the monthly excess returns on risk factor-mimicking portfolios for the whole period from July 1971 to December 2014, Column (4) – (8) report the cross correlations between factors. Panels B and C report the summary of risk factor-mimicking portfolios in increasing and decreasing sentiment periods, respectively

Factor	Monthly return	Std dev	Cross correlations						
			MRP	SMB	HML	MOM	RMW	CMA	SENT
Panel A: summary of risk factor-mimicking portfolios (all periods)									
MRP	0.53	4.57	1.00						
SMB	0.21	3.06	0.25	1.00					
HML	0.37	2.98	-0.31	-0.11	1.00				
MOM	0.70	4.40	-0.14	-0.03	-0.16	1.00			
RMW	0.29	2.23	-0.23	-0.39	0.15	0.08	1.00		
CMA	0.35	1.98	-0.39	-0.05	0.70	0.03	-0.02	1.00	
SENT	0.02	2.03	0.39	0.04	-0.17	-0.25	-0.18	-0.17	1.00
Panel B: summary of risk factor-mimicking portfolios (increasing sentiment periods)									
MRP	2.47	4.07	1.00						
SMB	0.53	3.01	0.16	1.00					
HML	0.01	2.97	-0.33	-0.06	1.00				
MOM	0.21	4.90	-0.18	-0.16	-0.16	1.00			
RMW	0.14	2.20	-0.22	-0.39	0.07	0.18	1.00		
CMA	0.07	1.99	-0.40	-0.05	0.69	0.01	-0.09	1.00	
SENT	0.39	2.29	0.37	0.05	-0.15	-0.37	-0.19	-0.18	1.00
Panel C: summary of risk factor-mimicking portfolios (decreasing sentiment periods)									
MRP	-1.38	4.23	1.00						
SMB	-0.11	3.08	0.29	1.00					
HML	0.72	2.96	-0.26	-0.14	1.00				
MOM	1.17	3.78	0.00	0.17	-0.19	1.00			
RMW	0.43	2.26	-0.22	-0.39	0.22	-0.05	1.00		
CMA	0.63	1.93	-0.33	-0.02	0.70	0.01	0.04	1.00	
SENT	-0.35	1.66	0.33	-0.02	-0.17	0.01	-0.15	-0.11	1.00

Table 1.9
Regressions for Equal-weighted Correlation Portfolios: July 1971 to December 2014

This table reports the regression results of portfolio monthly excess returns on the market sentiment factor and other risk factors. At the end of June of year t, stocks are allocated into 10 equal-weighted portfolios on the basis of their correlations between their return and market sentiment. Stock returns are collected from CRSP from 1967 to 2014. The correlation, ρ, is calculated using 48 monthly returns ending in June of year t. We further divide the top and bottom portfolios into thirds to investigate the properties of extreme portfolios; A (C) denotes low (high) correlation with sentiment. We sort all firms on their correlations into three portfolios, using 30% and 70% breakpoints, and define market sentiment factor (SENT) as the difference of portfolio excess returns between the top and bottom portfolios. The risk factors, MRP, SMB, HML, RMW, CMA and MOM are collected from Kenneth R. French's data library on monthly basis. *, **, and *** indicate significance at 5%, 1%, and 0.1% level, respectively. We estimate the following factor model: $R_{p,t} - R_{f,t} = \alpha_p + \beta_{1,p}MRP_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}RMW_t + \beta_{5,p}CMA_t + \beta_{6,p}MOM_t + \beta_{7,p}SENT_t + \varepsilon_{p,t}$.

Portfolio	Constant	MRP	SMB	HML	MOM	RMW	CMA	SENT	Adj R^2
1A	0.25**	0.93***	0.72***	0.15***	-0.19***	-0.02	0.08	-1.01***	0.860
	(2.64)	(40.00)	(22.58)	(3.43)	(-8.80)	(-0.49)	(1.13)	(-20.62)	
1B	0.29**	0.98***	0.79***	0.27***	-0.18***	-0.02	-0.01	-0.92***	0.867
	(2.98)	(40.79)	(24.15)	(5.85)	(-8.27)	(-0.35)	(-0.21)	(-18.41)	
1C	0.39***	1.01***	0.78***	0.23***	-0.19***	-0.02	-0.01	-0.87***	0.874
	(4.03)	(42.53)	(24.08)	(5.16)	(-8.43)	(-0.46)	(-0.19)	(-17.52)	
1(low)	0.31***	0.97***	0.77***	0.22***	-0.19***	-0.02	0.01	-0.93***	0.920
	(4.30)	(54.67)	(31.44)	(6.51)	(-11.33)	(-0.60)	(0.25)	(-25.00)	
2	0.29***	1.00***	0.83***	0.14***	-0.19***	-0.03	0.11*	-0.73***	0.929
	(4.08)	(56.84)	(34.47)	(4.09)	(-11.64)	(-1.03)	(2.26)	(-20.02)	
3	0.33***	0.99***	0.76***	0.19***	-0.17***	-0.03	0.04	-0.49***	0.927
	(4.77)	(56.89)	(31.95)	(5.88)	(-10.42)	(-0.98)	(0.87)	(-13.50)	
4	0.32***	0.97***	0.82***	0.16***	-0.21***	-0.06	0.06	-0.23***	0.924
	(4.23)	(52.33)	(32.18)	(4.60)	(-11.90)	(-1.56)	(1.05)	(-5.95)	
5	0.30***	0.99***	0.80***	0.15***	-0.18***	-0.07*	0.03	-0.26***	0.940
	(4.53)	(60.71)	(35.67)	(4.67)	(-11.81)	(-2.31)	(0.72)	(-7.61)	
6	0.29***	0.99***	0.79***	0.15***	-0.18***	-0.08*	0.07	-0.10**	0.937
	(4.26)	(58.19)	(34.03)	(4.66)	(-11.47)	(-2.30)	(1.44)	(-2.81)	
7	0.28***	0.97***	0.79***	0.14***	-0.16***	-0.05	0.12**	0.06	0.941
	(4.34)	(59.66)	(35.64)	(4.43)	(-10.49)	(-1.59)	(2.60)	(1.79)	
8	0.31***	0.99***	0.79***	0.16***	-0.20***	-0.01	0.15**	0.13***	0.947
	(4.95)	(63.22)	(36.63)	(5.27)	(-13.53)	(-0.28)	(3.29)	(4.02)	
9	0.31***	0.97***	0.79***	0.19***	-0.18***	-0.08*	0.02	0.30***	0.944
	(4.67)	(58.31)	(34.61)	(6.06)	(-11.92)	(-2.39)	(0.45)	(8.74)	
10 (high)	0.30***	0.99***	0.78***	0.20***	-0.16***	-0.00	0.00	0.41***	0.945
	(4.45)	(59.44)	(33.87)	(6.33)	(-10.44)	(-0.02)	(0.02)	(11.76)	
10A	0.32***	0.97***	0.77***	0.16***	-0.16***	-0.00	0.03	0.34***	0.924
	(4.16)	(50.48)	(29.06)	(4.35)	(-9.02)	(-0.11)	(0.58)	(8.40)	
10B	0.25**	0.99***	0.81***	0.24***	-0.12***	0.02	0.03	0.39***	0.930
	(3.24)	(52.81)	(31.30)	(6.72)	(-6.65)	(0.65)	(0.61)	(9.93)	
10C	0.33***	1.01***	0.75***	0.20***	-0.21***	-0.02	-0.06	0.50***	0.902
	(3.45)	(42.79)	(23.11)	(4.54)	(-9.46)	(-0.44)	(-0.91)	(10.12)	
10–1	-0.01	0.02	0.01	-0.02	0.03*	0.02	-0.01	1.34***	0.860
	(-0.18)	(1.43)	(0.42)	(-0.80)	(2.13)	(0.80)	(-0.32)	(49.78)	
10C–1A	0.08	0.08**	0.02	0.05	-0.02	0.00	-0.14	1.51***	0.675
	(0.76)	(2.89)	(0.69)	(1.03)	(-0.67)	(0.04)	(-1.82)	(27.39)	

Table 1.10
SENT Loadings in Fama-French Three-, Four, and Five-Factor Models

This table reports the SENT loadings in sentiment-augmented three-, four-, and five-factor models. The three-factor model contains MRP, SMB and HML. The five-factor model contains RMW (robust minus weak profitability) and CMA (low minus high investment) in addition to the Fama-French three factors. We omit HML in the sentiment-augmented four-factor model. At the end of June of year t, stocks are allocated into ten equal-weighted portfolios on the basis of their correlations between their return and market sentiment. Monthly stock returns are collected from CRSP from 1967 to 2014.The correlation, ρ, is calculated using 48 monthly returns ending in June of year t. We sort all firms on their correlations into three portfolios, using 30% and 70% breakpoints, and define the market sentiment factor (SENT) as the difference of portfolio excess returns between the top and bottom portfolios. MRP, SMB, HML, MOM, RMW, and CMA are collected from Kenneth R. French's data library on monthly basis. *, **, and *** indicate significance at 5%, 1%, and 0.1% level, respectively.

Portfolio	Three-Factor	Four-Factor	Five-Factor
1(low)	-0.83***	-0.93***	-0.83***
2	-0.63***	-0.72***	-0.64***
3	-0.40***	-0.48***	-0.40***
4	-0.11**	-0.22***	-0.12**
5	-0.15***	-0.25***	-0.17***
6	0.01	-0.09*	-0.01
7	0.16***	0.07*	0.14***
8	0.24***	0.14***	0.24***
9	0.41***	0.32***	0.40***
10 (high)	0.50***	0.41***	0.50***
10−1	1.33***	1.34***	1.33***

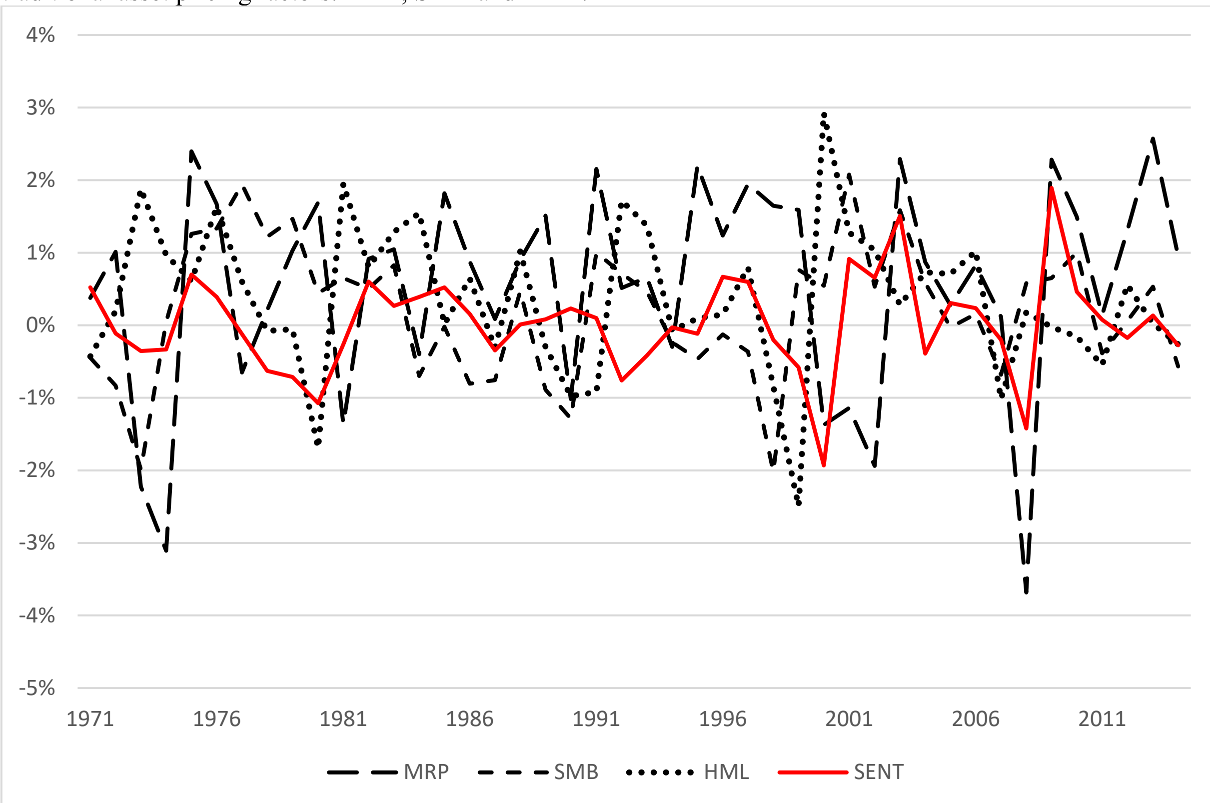
Table 1.11
SENT Loadings for Portfolios Sorted on Firm Characteristics

This table reports the SENT loadings in the sentiment-augmented model for portfolios sorted on size, book-to-market ratio, operating profitability, investment, and institutional holdings. At the end of June of year t, we sort all firms in our sample based on their correlations between return and market sentiment into three portfolios, using 30% and 70% breakpoints, and define the market sentiment factor (SENT) as the difference of portfolio excess returns between the top and bottom portfolios. The correlation, ρ, is calculated using 48 monthly returns ending in June of year t. We obtain these portfolios directly from Kenneth R. French's data library except for the institutional-ownership portfolios that are formed using our sample. The risk factors, MRP, SMB, HML, RMW, CMA, and MOM are also from Kenneth R. French's data library. *, **, and *** indicate significance at 5%, 1%, and 0.1% level, respectively. We estimate the following factor model: $R_{p,t} - R_{f,t} = \alpha_p + \beta_{1,p} MRP_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \beta_{4,p} RMW_t + \beta_{5,p} CMA_t + \beta_{6,p} MOM_t + \beta_{7,p} SENT_t + \varepsilon_{p,t}$.

Portfolio	Size	Book-to-Market	Operating Profitability	Investment	Institutional Holdings
1 (low)	-0.40***	-0.30***	-0.48***	-0.45***	-0.50***
2	-0.00	-0.13**	-0.21***	-0.18***	-0.35***
3	0.04	-0.15***	-0.15***	-0.14***	-0.36***
4	0.08**	-0.13***	-0.06*	-0.06*	-0.25***
5	0.12***	-0.11***	-0.06*	-0.08**	-0.12**
6	0.09**	-0.08**	-0.09***	-0.04	-0.09**
7	0.13***	-0.12***	-0.06*	-0.05	-0.04
8	0.12***	-0.07*	-0.07**	-0.11***	0.03
9	0.08**	-0.18***	-0.05	-0.13***	0.09**
10 (high)	0.00	-0.35***	-0.15***	-0.24***	0.15***
10–1	0.41***	-0.05	0.33***	0.22***	0.66***

Figure 1.1
Magnitudes of Risk Factors

This figure shows average monthly premiums of SENT factor in comparison with average monthly premiums on traditional asset pricing factors: MRP, SMB and HML.



Chapter 2
Does it Pay to Know More About Your Neighbors: Evidence from Local Taxi Trips

2.1 Introduction

Institutional investors are in constant and substantial efforts to meet privately with publicly traded firms to pursue proprietary information. While Regulation Fair Disclosure (Reg FD) bans public firms from disclosing material information to select parties, it does not explicitly prohibit private meetings with investors. Academics have long been interested in how investors benefit from their private meetings with corporate insiders. However, the empirical identification of private meetings is difficult because neither investors nor firms in the U.S. are obligated to record or report their offline communications. In response, academics resort to indirect proxies for private meetings. One approach is to focus on public corporate events, such as conferences and analyst/investor days, that provide opportunities for private face-to-face meetings between market participants and corporate insiders (Bushee, Jung and Miller (2017), Green, Jame, Markov and Subasi (2014a, b), and Kirk and Markov (2016)). However, as pointed out in Bushee, Gerakos and Lee (2018), these meetings occur at public events that are well-scheduled in advance and, therefore, non-participants are likely to be aware of the occurrence of such meetings.

Another approach uses geographic proximity to proxy for the likelihood of private meetings among local economic agents. When rooted in the same community, mutual fund managers and local corporate insiders may run into each other repeatedly at neighborhood shops, cafes, community centers, libraries, and recreational areas and, subsequently, have a better chance of having direct contact with one another. Consistently, several studies provide evidence of private information flow among local agents. For example, Coval and Moskowitz (1999) find that U.S. mutual fund managers strongly prefer locally headquartered firms. Further, Coval and Moskowitz (2001) and Pool, Stoffman and Yonker (2012) show that on average mutual fund managers earn a greater abnormal return from their local holdings compared to their distant holdings. Although geographical proximity could serve as indirect proxies for potential private interactions, these studies provide no evidence as to how local economic agents interact with each other.

In this study, we bridge the two approaches and fill the gap in the literature by focusing on one important form of private interactions: in-house meetings between local mutual fund managers and corporate insiders. Specifically, we investigate whether in-house meetings are associated with an informational advantage for the participating investors. Investors may benefit from in-house meetings in several ways. First, they may have the opportunity to communicate face-to-face with high-rank officers. Even though the Regulation Fair Disclosure prohibits selective disclosure of material information by corporate insiders, investors could still fill in their mosaic by compiling nonmaterial yet nonpublic information, as argued in Solomon and Soltes (2015), such as body languages, shifts in emphasis in describing the business strategy, or tone stock buyback plans, etc. Second, besides meeting executive officers, investors in attendance may also observe the firm's operation and employee morale, through which they can obtain a first-hand assessment of the financial conditions of the firm. Therefore, investors who are not involved are likely to be at an informationally disadvantaged position.

As U.S. firms and investors are not required to record or report their private in-house meetings, we identify such unobservable interactions by exploiting the taxi records in New York City (NYC). Specifically, we determine a fund to be an NYC fund if its management company office is located in NYC and a firm to be an NYC firm if its headquarter is in NYC. We use the taxi trips that occur between NYC funds and NYC firms to proxy for private in-house meetings. The taxi trip data are collected from the NYC Taxi and Limousine Commission (TLC). TLC has publicly released over 1.3 billion taxi trip records from January 2009 onward, initially in response to a Freedom of Information Act request.

The taxi records in NYC provide a unique setting to overcome the limitations in prior literature on private meetings between corporate insiders and investors. First, not like corporate events that are publicized and even webcast, taxi trips are unobservable to non-passengers. Therefore, other market participants are not likely to anticipate these taxi-facilitated in-house meetings and modify their trading behaviors. In this regard, our approach is in spirit similar to Bushee, Gerakos and Lee (2018), who use corporate jet patterns to proxy for private meetings with investors. Second, these data allow us to identify the mutual fund managers, among all local managers, that are more likely to engage in private meetings. More importantly, rather than using stock market reactions to infer the impact of private meetings, we are able to analyze how such activities shape institutional investors' portfolios and whether they obtain value-relevant information from these meetings.

Our first set of tests focuses on whether mutual funds with more local taxi trips place greater investment in local firms. While previous literature on geographic proximity assumes that investors have equal access to local firms and treats them as homogeneous, we are able to identify the fund managers who are more actively engaged in in-house meetings, among all local funds managers. Specifically, we divide NYC funds into the "busy" and "unbusy" groups based on the number of taxi trips that occur between the fund and all NYC public firms in each quarter. We find that, while an average NYC fund place 8.71% of its assets on NYC equities and an average non-NYC fund place only 8.16%, the overweight by the "busy" funds is about two times as large as it is by the "unbusy" funds. The NYC overweight is 0.8% for the "busy" funds yet only 0.41% for the "unbusy" funds. Considering that on average non-NYC funds invest 8.16% of their AUM in NYC equities, 0.8% (0.41%) represents an overinvestment of 9% (5%) for the "busy" ("unbusy") funds compared to their non-NYC peers.

Coval and Moskowitz (2001) find that agile funds, in particular small, undiversified, and old funds, invest more heavily in local firms. This is because smaller funds with fewer holdings are better at monitoring local information and old funds are more likely to have established social connections with the local corporate insiders; therefore, these funds rely more on their proprietary information about local firms. Following their approach, we sort ”busy” and “unbusy” funds on size, number of holdings, and age and investigate whether in-house meetings matter more for agile funds. Consistently, we find that small, undiversified, and old “busy” funds exhibit greater NYC bias than “unbusy” funds in the same fund characteristic group, but the differences are weaker or even not significant for large, diversified, and young “busy”and “unbusy” funds.

Despite the significance of the NYC bias by the funds with more taxi trips, taxi trips are still likely to be a noisy proxy for private in-house meetings for two reasons. First, fund managers may visit the firm through other means, for example through walking. Second, these taxi trips might be taken by random travelers. To address the first concern, we next focus on the local firms that are beyond walking distance from the fund; arguably, taxi may represent a relatively more important transportation mode for fund managers to acquire information about firms that are farther from them. Specifically, we divide funds’ NYC holdings into “hyper-local” and “local-distant” portfolios based on the fund-firm distance. We find that NYC bias in the local-distant portfolios by the more-trip funds is significantly more than the bias by the fewer-trip funds, yet the difference is insignificant in the hyper-local portfolios.

To address the “random travelers” concern, we focus on the frequency of taxi trips. If the taxi trips have no relation with funds’ information acquisition activities, the frequency of trips may not matter at all for the degree to which the participating investors are informed. To investigate this conjecture, we split each NYC fund’s NYC holdings into “taxi trips” portfolio and “no trips” portfolio based on whether the fund has taxi trips to the firm in the previous quarter. We further split the “taxi trips” portfolio into “one trip” and “multiple trips” groups. Our results indicate that more trips lead to a greater local bias: while NYC funds place significantly greater bets in the “taxi trips” portfolio, they further overinvest more in the “multiple trips” portfolio than in the “one trip” portfolio.

Having established that private in-house meetings result in greater investment from local investors, we next investigate whether investors are able to extract value-relevant information from such activities. If the NYC bias of NYC funds were driven by proprietary information, the NYC positions of funds that are actively engaged in in-house meetings would generate greater abnormal returns. Consistently, we find that, while NYC funds outperform non-NYC funds on their NYC positions after adjusting for a number of risk factors, the outperformance comes solely from the "busy" NYC funds – they outperform non-NYC funds by nine basis points (1.08% per year). In contrast, the performance of the "unbusy" NYC funds does not differ from that of non-NYC funds. Further, we investigate whether the private information obtained through in-house meetings is reflected in funds' trading decisions. We show that the stocks that a fund purchases after visiting the firm generate greater abnormal returns than the stocks that the fund purchases without visiting.

Since in-house meetings appear to be informative, the trades made by the participating funds collectively should provide information about stock's future expected returns. Baik, Kang and Kim (2010) document a positive relationship between the change in ownership by local investors and future stock returns. We step further from their study by separating the informed local investors from the less informed local investor for each firm. Specifically, for every firm quarter, we divide a firm's NYC fund investors into those that have had taxi trips to the firm in the previous quarter and those that have not. We next aggregate the change in ownership in the firm by each type of investors. Our results indicate that future stock returns are positively related to the trades of funds that have met corporate insiders. A one-standard-deviation increase in ownership by these funds is associated with nine basis points of excess monthly return. In contrast, the trades of funds that have not had taxi trips have no predictive power.

Our final set of tests investigate the information content of in-house meetings. We focus on earnings announcement because it represents an important signaling channel that is used by managers to transmit information to the public and by investors to gauge the prospect of the firm. Should investors are able to acquire any information about earnings, they should conduct the visits before, rather than after, earnings announcement. Further, we expect that information asymmetry, proxied by earnings surprise, to be negatively associated with the number of taxi trips associated with the firm. Our results confirm our hypotheses. We find that abnormal trips mainly occur in the second week before announcement dates and that the number of taxi trips that a firm received is negatively associated with earnings surprises, indicating that such activities lead to a reduction in information asymmetry. A one-standard-deviation increase in the number of taxi visits is associated with 18% drop in absolute earnings surprise.

We contribute to the literature in several areas. First, we extend the literature on sources of institutional investors' informational advantage. Among the few papers that investigate private meetings between fund managers and corporate insiders, Bushee, Jung and Miller (2017) study the one-on-one meetings and breakout sessions with managers at invitation-only investor conferences. They document increased trade sizes when firms provide offline access and potential trading gains after the conference for these firms, suggesting that investors benefit from their private meetings with the management at the conferences. Similarly, Green, Jame, Markov and Subasi (2014a, b) show that access to management at broker-hosted conferences leads to more informative and accurate analyst forecasts and increased commission revenue for the hosting brokers. Cheng, Du, Wang and Wang (2016), Han, Kong and Liu (2017), and Kirk and Markov (2016) provide evidence of the informational effect of analyst/investor days. We add to the list by establishing in-house meetings as a private information flow channel and providing a potential way to identify fund managers who are likely to possess value-relevant proprietary information.

Direct identification of private meetings is empirically challenging. Closest to our work is Bushee, Gerakos and Lee (2018), who use corporate jet patterns to identify private "roadshow" meetings with investors and find that roadshows are associated with positive abnormal market reactions for the firm and more trading by institutional investors located in the roadshow area. Similar to their work, we also focus on the meetings that are not publicly announced and, therefore, not known to non-participants. However, our identification strategy is unique in uncovering private meetings and, more importantly, the participating parties. Further, with the taxi records data, we are able to examine directly the impact of these meetings on institutional investors' portfolios.

Second, we contribute to the literature on the local bias of institutional investors. While prior studies suggest that investors may obtain superior information about local firms through private meetings with the management, they do not provide direct evidence of such activities. In contrast, we provide a proxy for in-house meetings and show that such information acquisition activities lead to overinvestment in and abnormal return from local firms. Moreover, rather than treating local investors as homogeneous and presuming equal access to proprietary information for them, we show that only funds that are actively engaged in in-house meetings, among all local funds, have a greater likelihood of possessing superior information about local firms.

The remainder of this paper is organized as follows. Section II describes the data and presents summary statistics. Section III examines the performance of NYC portfolios across mutual funds, the effect of trading of NYC funds on future stock returns, and the relationship between in-house meeting and the information environment around firms' earnings announcement. Section IV concludes.

2.2 Data

2.2.1 Taxi Trip Records and In-house Meetings

The NYC Taxi and Limousine Commission (TLC) has publicly released over 1.3 billion taxi trip records from January 2009 onward, initially in response to a Freedom of Information Act (FOIA) request in 2014. TLC collects trip record information for three types of vehicles: medallion (yellow) taxi, street hail livery (green) taxi, and for-hire vehicles (FHVs) such as Uber and Lyft. The taxi trip records contain precise pick-up and drop-off GPS coordinates, pick-up and drop-off times, trip distance, number of passengers, tip amount, and fare amount. Starting in July 2016, TLC provides only the pick-up and drop-off zone IDs instead of GPS coordinates. TLC begins publishing FHV data in 2016, which contain only the time and zone ID of the pick-up and drop-off of the trip (only pick-up before 2017).

We rely on the yellow taxi records from January 2009 to June 2016 to identify in-house meetings because yellow taxis are licensed to pick up passengers anywhere in NYC, while green taxis are allowed to respond to street hails and calls only in Manhattan north of East 96th Street and West 110th Street and in all outer boroughs (Bronx, Brooklyn, Queens, and the Staten Island). Figure 1 shows that all NYC funds and almost all public firms held by mutual funds are located in the areas that are forbidden for green taxis. Despite the increasing popularity of Uber and Lyft, we cannot examine the FHV rides because of the lack of detailed trip records. However, this is not likely to impair our study because, as of June 2016 in Manhattan, taxis still make more than three times as many pickups per day than Ubers do (Schneider (2018)).

----- Insert Figure 2.1 -----

We use the pick-up and drop-off coordinates to identify in-house meetings. Specifically, we map the pick-up and drop-off locations to fund offices and firm headquarters. The taxi trip data are collected and provided to TLC by third-party technology service providers, and TLC cannot guarantee their accuracy (NYC Taxi & Limousine Commission 2017). Finer (2018) uses taxi trips to infer the interaction between insiders of the Federal Reserve Bank of New York and insiders of Major commercial banks. He shows that the taxi GPS coordinates are accurate to between O(10 ft) to O(100 ft) and that coordinates are mostly clustered within 100 feet of a block's border. We, therefore, map a taxi ride to an institution if the pick-up or drop-off coordinates fall within 30 meters (approximately 100 feet) from the institution. Since we are interested in the private interaction between mutual funds and public firms, we only keep the taxi trips that occur from the fund to the firm or vice versa. We treat multiple taxi rides between the same fund and firm within one day as one.

We sum all taxi trips between an NYC equity fund and all NYC public firms to get the number of in-house meetings that the fund has in each quarter. Table 2.1 shows that on average an NYC fund takes 210 taxi trips to all NYC public firms each quarter and 12 trips to NYC firms that are in its portfolio. Note that we do not claim that taxi trips capture all private fund-firm interaction, but rather that they increase the probability of having in-house meetings. It is possible that these taxi trips between funds and firms are taken by random travelers, but this possibility only biases our results toward finding nothing.

2.2.2 Stock Data

We link each stock holding in the Thompson Reuters Mutual Fund Holdings database to the CRSP U.S. stock database and the Compustat for stock returns and firm characteristics. We obtain the historical firm headquarter address from the Compustat Snapshot database. After matching with the fund holdings data, we identify 433 (244) public companies over the period 2000-2017 (2009-2016) that are headquartered in NYC. We further obtain the analyst following and forecast data for these companies from the I/B/E/S database.

2.2.3 Mutual Fund Data

We combine several mutual fund databases in this study. We use the Thompson Reuters Mutual Fund Holdings database for the stock holdings of U.S. mutual funds. We use the CRSP Survivor-Bias-Free U.S. Mutual Funds database for information on total net assets, Lipper classification code, management company address, and other fund attributes. To focus on domestic active equity funds, we include funds with the following Lipper classification codes: large-cap core, large-cap growth, large-cap value, mid-cap core, mid-cap growth, mid-cap value, multi-cap core, multi-cap growth, multi-cap value, small-cap core, small-cap growth, small-cap value, and equity income. Following Pool, Stoffman and Yonker (2015), we exclude funds with fewer than 20 holdings or more than 500 holdings since funds with more than 500 holdings are likely to be index funds. In addition, we exclude funds with TNA less than $5 million and funds with an average investment less than 80% of TNA in equity. Finally, we eliminate funds with missing management address in CRSP. For every quarter, we define a fund as NYC fund if its management company office is located in New York City. Since the data on mutual fund management address are available after 1999, our final sample consists of 2988 funds (582 NYC funds and 2409 non-NYC funds) from 2000 to 2017.

-----Insert Table 2.1-----

Table 2.1 reports the summary statistics of the mutual fund sample. The mean asset under management (AUM) of NYC funds is $1,097.20 million, which is smaller than that of non-NYC funds ($1588.50 million). However, the median AUM for NYC funds and non-NYC funds are $371.40 million and $232.70 million. This is due to some giant funds outside NYC. For example, the total net assets of the Fidelity Contrafund, located in Boston, MA, and the Growth Fund of America, located in Los Angeles, CA, are $124 billion and $177 billion as of December 31, 2017.

Though on average both NYC and non-NYC funds invest in seven equities in NYC, the average ownership in NYC holdings is significantly greater for NYC funds. Panel A in Table 2.2 shows that NYC funds invest 9.90% AUM in NYC equities over 2000-2017, while non-NYC funds invest only 9.19%. Since the NYC taxi records are only available after 2009, we further split our sample period into 2000-2008 and 2009-2017 to test the persistence of NYC bias. The difference is significant for both the first and second half of our sample period. To make sure this result is not driven by a subset of the NYC stocks, we exclude index constituents or financial stocks and repeat the comparison. Panel B in Table 2.2 shows that NYC bias is significant and robust with the subsets of NYC firms. NYC bias becomes 0.61% (0.48%) after excluding Dow 30 stocks (S&P 100); The NYC bias in non-financial firms and financial firms are 0.60% and 0.21%, respectively.

-----Insert Table 2.2-----

2.3 Empirical Tests

2.3.1 NYC Overweight and Fund Attributes

Prior literature shows that certain types of mutual funds may possess superior local stock selection abilities and exhibit greater local bias. For example, Coval and Moskowitz (2001) find that agile funds – small, undiversified, and old funds – invest more heavily in local stocks. Following Coval and Moskowitz (2001), we sort funds into quintiles based on size, number of holdings, and age in the previous quarter and examine the degree of NYC ownership for both NYC funds and non-NYC funds in different attribute quintiles.

-----Insert Table 2.3-----

In Table 2.3 Panel A we show that, for the sample period 2000-2008, small and medium NYC funds exhibit greater NYC bias than large NYC funds. The NYC funds in the smallest and middle size quintiles invest 0.61% and 1.05% more in NYC equities than non-NYC funds in the same size quintile, while the NYC funds in the largest quintile overinvest only by 0.26% and the difference is insignificant. The results are similar when we sort funds on the number of holdings. Undiversified NYC funds – those with the least number of holdings – invest 2.22% more in NYC equities than undiversified non-NYC funds, while the difference between diversified NYC and non-NYC funds is insignificant. NYC funds in the middle holdings quintiles exhibit a moderate overinvestment, 0.82%. The results with fund age show that both young and old funds exhibit a similar level of NYC bias. Young (old) NYC funds invest 1.72% (1.83%) more in NYC stocks than non-NYC young funds. Table 2.3 Panel B repeats the analysis for the period 2009-2017. The results are qualitatively similar. Funds in the smallest size quintile and the least holdings quintiles significantly overinvest in NYC equities by 0.83% and 1.11% respectively, while the NYC funds in the largest size and holdings quintiles exhibit negative and significant NYC biases (-0.37% and -1.53%). Overall, we show that small and undiversified NYC funds exhibit greater NYC bias. Our findings are consistent with Coval and Moskowitz (2001), who argue that "…small funds with few holdings are likely better able to monitor local information and pursue active tradings strategies."

2.3.2 Investment in NYC Equities and In-house Meetings

In this section, we investigate the relationship between in-house meetings and holdings and investment performance in NYC equities. The main hypothesis of our study is that local investors are able to obtain private information by meeting local firms. Therefore, rather than assuming an equal informational advantage among local investors, we hypothesize that funds that meet local firms more often are more likely to possess superior information about local firms. Since we use taxi trips between fund and firm to proxy for in-house meetings, we expect that funds with more taxi trips exhibit greater local bias and earn abnormal returns on their local portfolios.

2.3.2.1 NYC Bias and Taxi Trips

To begin, we divide NYC funds into the ”busy” and ”unbusy” groups based on the number of taxi trips. Specifically, we compute the quarterly number of taxi trips between an NYC fund and all NYC public firms and define a fund as "bush" (”unbusy”) if it has more (fewer) than the cross-sectional median. We calculate the NYC bias for fund i at the end of quarter t as follows:

$$NYC\ Bias_{i,t} = \sum_{k=1}^{K} w_{i,t}^{k} - \frac{\sum_{j}^{J} \sum_{k=1}^{K} w_{j,t}^{k}}{J}$$

where K is the set of stocks that are held by at least one mutual fund and are located in NYC, and I and J are the set of NYC and non-NYC mutual funds in the same Lipper Class. $w_{i,t}^{k}$ and $w_{j,t}^{k}$ are the portfolio weights applied to fund i and j's NYC holdings. The difference between fund i's NYC ownership and the average NYC ownership of non-NYC funds in the same Lipper class is our NYC bias measure, revealing the degree to which an NYC manager invests locally in excess of what a non-NYC manager invests.

-----Insert Table 2.4-----

Table 2.4 reports the magnitude of NYC bias for NYC funds across various attributes. Panel A shows that both "busy" and "unbusy" funds place greater bets in NYC equities than their non-NYC peers. However, "busy" funds significantly invest more in NYC equities than do "unbusy" funds. The NYC bias is 0.8% for "busy" funds yet only 0.41% for "unbusy" funds. Considering that on average non-NYC funds invest 8.16% of their AUM in NYC equities over 2009-2017, 0.8% (0.41%) represents an overinvestment of 9% (5%) for "busy" ("unbusy") funds compared to their non-NYC peers. We further break NYC funds into small and large, undiversified and diversified, and young and old fund categories using the median total net assets, number of holdings, and fund age in each quarter as breakpoints. Table 2.4 Panel B shows that small "busy" funds exhibit an NYC bias of 0.93%, while small "unbusy" funds have a mean bias of only 0.25%. The bias difference between large "busy" funds and large "unbusy" funds is, however, small (0.09%) and not significant. Panel C shows that undiversified "busy" funds exhibit a greater NYC bias than undiversified "unbusy" funds (1.15% V.S. 0.67%), while the difference between the diversified is significant yet smaller at 0.30%. Panel D shows that old "busy" funds exhibit a greater bias than old "unbusy" funds; the difference is 0.58% and is significant at the 1% level. We do not find a significant difference between young "busy" and "unbusy" funds. This result is consistent with Coval and Moskowitz (2001), where the authors argue that old funds are more likely to be socially connected and, therefore, have a better chance to obtain information via private meetings. Overall, these results are consistent with the information story that funds with more in-house meetings exhibit greater local bias.

2.3.2.2 NYC Bias and Fund-Firm Distance

A concern may arise from the fact that almost all public NYC firms and mutual funds are located in the Manhattan neighborhood. As a result, fund managers may not need the take a taxi to visit the firm – they can simply take a walk. Arguably, if this is the case, taxi trips may be a more important transportation mode and, therefore, more effective in capturing in-house meetings when the firms are beyond walking distance. We divide funds' NYC holdings into "hyper-local" and "local-distant" portfolios based on the fund-firm distance and examine whether funds with more taxi trips are associated with greater bias in the local-distant portfolio that contains firms beyond walking distance. We use 0.5 miles (0.75 miles) as the distance breakpoint because they approximate 10-minute (15-minute) walk in NYC. We compute NYC bias in each distance bucket as the difference between the fraction of fund assets in stocks in a distance bucket and the fraction of the market capitalization that resides in the same distance bucket. We use the market capitalization portfolio as a benchmark because the NYC holdings of non-NYC funds cannot be split into such distance portfolios.

-----Insert Table 2.5-----

Table 2.5 reports the NYC bias in different distance buckets for “busy” and “unbusy” funds. Panel A shows that “busy” funds do not exhibit greater bias in either the hyper-local or the local-distant portfolio than do “unbusy” funds. However, after excluding Dow 30 stocks, we show in Panel B that, while ”busy” and “unbusy” funds display a similar magnitude of NYC bias in their hyper-local portfolios, taxi trips do affect funds’ investment decisions in their local-distant portfolios. Using 0.5 miles as the distance breakpoint, the NYC overweighting in the local-distant portfolio by “busy” funds is significantly more the overweighting by “unbusy” funds (0.69% V.S. 0.49%); the difference becomes even larger (0.25%) when we use 0.75 miles to form distance portfolios. These results indicate that taxi trips are indeed an effective proxy for private interactions between the firm and the fund.

One possible explanation for the insignificant results in Panel A is that “unbusy” funds may be closet indexers. Since they are not as active as “busy” funds in acquiring private information, they may not engage in as much active management and wind up with investing in large firms with the least information asymmetry – especially those that are index constituents like Dow 30 stocks. Cremers and Petajisto (2009) document a trend of an increased fraction of closet indexers but decreased active management among actively managed mutual funds from 1980 to 2003. Consistent with their findings, our results imply that “unbusy” funds are likely to have low active management shares.

2.3.2.3 NYC Bias and Frequency of Taxi Trips

NYC is one of the busiest and most visited cities, thus it is possible that our in-house meeting proxy is impaired by some random travelers. We address this concern by investigating the relation between NYC bias and the frequency of taxi trips. If these random travelers count for a large portion in our taxi trips data, we should expect that the frequency of trips has no impact on the magnitude of NYC bias at all. We proceed by splitting the NYC holdings of NYC funds into two portfolios, "taxi trips" and "no trips," based on the number of taxi trips to each firm. We further divide the "taxi trips" portfolio into two subgroups, "one trip" and "multiple trips."

-----Insert Table 2.6-----

Table 2.6 reports the NYC bias for portfolios formed on the number of taxi trips. Panel A shows that, though both NYC funds exhibit positive local bias in both "taxi trips" and "no trips" portfolios, their investments in the former is significantly greater by 0.46%. Further, within the "taxi trips" portfolios, NYC funds overinvest in the "multiple trips" portfolios than in the "one trip" portfolios by 0.43%.

We have shown in Table 2.4 that certain types of funds – small, undiversified, and old funds– appear to rely more on in-house meetings. In this section, we continue this test by examining whether the frequency of taxi trips matters more for these funds. We divide NYC funds into large and small, diversified and undiversified, and old and young funds using the median total net assets, number of holdings, and fund age. Panel B shows that large NYC funds, unlike small NYC funds, do not exhibit greater local bias in the "taxi trips" portfolio than in "no trips." In contrast, small funds exhibit an NYC bias of 2.63% in "taxi trips," which is 0.84% greater than their bias in "no trips" (1.79%). Further, as shown in Column 4-6 in Panel B, though both large and small funds exhibit greater overinvestment in the "multiple trips" portfolios than in the "one trip" portfolios, this difference (0.52%) is larger for small funds. Panel C reports the results for the diversified and undiversified funds. While diversified funds do not show a preference between firms with trips and firms without, undiversified funds place significantly more assets in firms with trips. Among the firms that undiversified funds met, they further exhibit greater bias in firms with multiple trips than in firms with one trip. Panel D shows that both old funds and young funds invest more in firms with trips than firms without meetings. Within the firms with trips, both types of funds show preference in firms with multiple trips over firms with one trip.

To summarize, we show that NYC funds determine their investments in NYC firms based on the information obtained through in-house meetings. Our results suggest that the more information they acquire the greater local bias they exhibit. Further, funds that are better at monitoring local information – small and undiversified funds – rely more heavily on company sites to obtain information.

2.3.2.4 Performance of NYC Positions and Taxi Trips

Thus far, our results have shown a greater NYC bias among the mutual funds that are more actively engaged in in-house meetings. Next, we investigate whether these funds are able to obtain value-relevant information from these meetings. To begin, we test whether NYC funds, in general, outperform non-NYC funds on their NYC positions. Next, we examine whether "busy" funds earn greater abnormal returns on NYC positions than do "unbusy" funds because of the greater likelihood of informational advantage.

Estimation is conducted using pooled ordinary least squares regression. The results are reported in Table 2.7. The dependent variable is the value-weighted excess returns on NYC positions for each fund ($R_{NYC,i} - R_f$). We control for the market risk premium, the Fama-French-Carhart factors (SMB, HML, UMD), total net assets, age, and number of holdings. In all specifications, we include quarter dummies and Lipper Class dummies to control for time, and investment style fixed effect. We cluster standard errors at the fund level to adjust for heteroscedasticity.

Column 1 includes only market risk premium and NYC Fund dummy that equals one if the fund is located in NYC. We show that NYC funds on average earn an excess monthly return of five basis point (0.6% per year) on their NYC positions compared to non-NYC funds after adjusting for the market beta. Further, we break down NYC funds into "busy" and "unbusy" funds in Column 2. We find that the outperformance comes solely from "busy" NYC funds – they outperform non-NYC funds by nine basis points (1.08% per year). "unbusy" NYC funds underperform non-NYC funds by six basis points, but the difference is insignificant. In Column 3 – 5, we further adjust for other risk factors and fund characteristics. The outperformance of NYC funds, especially "busy" funds, is robust to different model settings.

-----Insert Table 2.7-----

Since all NYC funds in our sample are in Manhattan, one may argue that these funds may have better information about investment opportunities nationwide, rather than just NYC firms, because they are located in the financial center of the country. We examine this possibility by taking the return gap between a fund's NYC positions and non-NYC positions ($R_{NYC,i} - R_{non-NYC,i}$) and regress on the set of control variables defined in Table 2.7. If NYC funds have a comparative informational advantage only on NYC firms, we should expect the return difference to be greater for these funds. Further, we expect the return gap to be wider for INF funds should in-house meetings represents a crucial channel to obtain private information about local firms.

-----Insert Table 2.8-----

Column 1 in Table 2.8 shows that on average the return gap for NYC funds is greater than non-NYC funds by five basis points (0.60% per year). Further, Colum 2 shows that INF funds earn significant greater returns on their NYC positions than on non-NYC positions. The return gap is

12 basis points (1.44% per year) and significant at the 1% level. In contrast, there is no significant difference between the performance of LINF funds and non-NYC funds. Column 3 – 5 show similar results after controlling for other risk factors and fund characteristics. This evidence indicates that the outperformance of NYC funds and, especially INF funds, is not due to characteristics associated with NYC.

Coval and Moskowitz (2001) and Ivkovic and Weisbenner (2005) show that local investors earn greater returns on local holdings than distant holdings. We confirm their findings and, more importantly, advance the literature by showing that only funds that are actively engaged in acquiring local information profit from their local positions.

2.3.2.5 Trades of NYC Funds and Taxi Trips

We have thus far considered the NYC positions of mutual funds; our findings suggest that funds are able to obtain incremental private information through visiting local firms. If this is the case, we should expect that the trades that investors make after meeting the managers are more profitable than the trades without meeting.

To investigate this conjecture, we first split each fund's NYC holdings into "BUY," "SELL," and "HOLD" portfolios based on the quarterly change in the number of shares owned in each stock. We next divide each portfolio into "taxi trips" and "no trips" groups based on the number of taxi trips between the fund and the firm in the previous quarter. If managers obtain private information through in-house meetings, the stocks they buy after meeting should outperform those without meeting. In the same way, the stocks they sell after meeting should underperform those without.

-----Insert Table 2.9-----

We compute the value-weighted portfolio returns for the "taxi trips" and "no trips" stocks and compare the return difference in Table 2.9. Column 1 – 3 report the results for BUY portfolios. Column 1 shows that the "taxi trips" portfolio outperforms the "no trips" portfolio by 4.57% per month. Column 2 shows that, after adjusting for the market beta, the outperformance drops to 4.23%. Column 3 shows that, after adjusting for all Fama-French-Carhart factors, the "taxi trips" portfolio still outperforms the "no trips" by 1.66%. Column 4 – 6 reports the results for the SELL portfolios. Though the "taxi trips" portfolio underperforms the "no trips" portfolio, the difference is statistically discernible. One possible explanation is that firms are reluctant to share bad news with local investors. Hong, Lim and Stein (2000) argue that bad news diffuses only gradually across the investing public. Similarly, Kothari, Shu and Wysocki (2009) also suggest that management, on average, delays the release of bad news to investors.

2.3.3 Trading of Informed Local Institutional Investors and Future Returns

In this section, we shift our focus from the fund manager to the stock. Gompers and Metrick (2001) argue that the level of institutional ownership serves as a good proxy for institutional demand, while the change in institutional ownership is a good indicator for informational advantage. Further, as we have discussed in previous sections, only NYC funds that conduct in-house meetings appear to have private information about local firms. Taken together, the change in ownership of the meeting funds, rather than NYC funds that are not engaged in such activities, should contain information about the stock's future returns.

To investigate this conjecture, we begin by identifying informed local mutual fund investors for each NYC firm. For every firm quarter, we divide a firm's NYC fund investors into those that have visited the firm in the previous quarter and those that have not. We then aggregate the change in ownership for both types of NYC fund investors at the firm level, rescaled with total ownership in the previous quarter. Specifically, we compute the quarterly trades made by each type of mutual funds as:

$$Trade_{i,t}^{T} = \log(2 + \frac{\sum_{j=1}^{J} \Delta Shares_{j,t}^{T}}{\sum_{j=1}^{J} Shares_{j,t-1}^{T}}), \text{ and}$$
$$Trade_{i,t}^{NT} = \log(2 + \frac{\sum_{j=1}^{J} \Delta Shares_{j,t}^{NT}}{\sum_{j=1}^{J} Shares_{j,t-1}^{NT}}),$$

where i and j denote NYC firms and NYC funds, respectively, T and NT indicate whether or not the fund has taxi trips to the firm. We add two to the percentage change in ownership because it is possible that the NYC investors of a firm may clear their position, resulting in a change of -100%.

-----Insert Table 2.10-----

Table 2.10 reports the regression results. Column 1 shows that future returns are positively related to the trade of funds that have visited the firm, yet Column 2 shows a negative relation between future returns and the trade of funds without visiting. A one-standard-deviation increase in ownership by visiting NYC funds is associated with an increase of 0.3 in $Trade^{T}$, which translates into nine basis points of excess monthly return. Untabulated results show that stock returns in the current quarter are positively related to the trade of funds without visiting. These results are consistent with the flow-based temporary price hypothesis. Ben-Rephael, Kandel and Wohl (2011) show that fund flows are positively correlated with market returns, and that 85% (all) of the positive relationship between the net exchanges of equity funds and aggregate stock market excess returns is reversed within four (ten) months. Lou (2012) finds that flow-induced trading positively forecasts returns, which are then reversed subsequently. To summarise, our results indicate that not all local funds possess informational advantage on local firms – only those who visit local firms to acquire information do. Not surprisingly, we find that the trade of funds without visiting lose explanatory power in Column 3 when we include the trades of both types of NYC funds as the independent variables. In Column 4 we include the trade difference between funds with and without visiting as an explanatory variable and find that it is positively related to future stock returns.

2.3.4 Earnings Forecasts and In-house Meetings

While previous analyses have shown that in-house meeting plays a crucial role in the informational advantage of local investors, little is known about the information content of these private interactions. In this section, we shed light on this question by focusing on earnings announcement because it represents an important signaling channel that is used by managers to transmit information to the public and by investors to gauge the prospect of the firm. Our analysis regarding the information content to earnings announcement is twofold. First, we investigate the timing of taxi trips around earnings announcement dates. Second, we study the effect of such meetings on the magnitude of earnings surprise.

-----Insert Table 2.11-----

Table 2.11 reports the analysis of the timing of in-house meetings relative to earnings announcement dates. The dependent variables in Column (1) and (2), (3) and (4), and (5) and (6) are the natural logarithm of the number of in-house meetings that a firm has over one-month, two-week, and one-week window, respectively, around the earnings announcement date. To avoid overlapping time window, we include only taxi trips that occur from 30 days before the announcement to 30 days after the announcement. The main variable of interests are the dummy variables indicating the time windows relative to earnings announcement dates. *Month -1* dummy equals one if the time window is from day t-30 to day t-1 and zero if from day t+1 to day t+30. *Week -2 to -1* dummy indicates the time window of t-14 to t-1. *Week -4 to -3* dummy indicates the time window of t-28 to t-15. *Week -1* dummy indicates the time window of t-7 to t-1. *Week -2* dummy indicates the time window of t-14 to t-8. *Week -3* dummy indicates the time window of t-21 to t-15. *Week -4* dummy indicates the time window of t-28 to t-22. To control for of firm characteristics that relate to a firm's information environment, we follow Bushee, Gerakos and Lee (2018) and include firm size (*Log MVE*), book-to-market ratio (*BM Ratio*), sales growth (*Sales Growth*), leverage ratio (*Leverage*), earnings per share scaled by price (*EP Ratio*), the change in net income (*△Earn*), analyst following (*Log # Analyst*).

Column 1 and 2 show that local mutual fund managers take significantly more taxi visits to local firms before earnings announcement than after. In Column 3 and 4 (5 and 6), we decompose the one-month window before announcement into bi-weekly (weekly) windows. We find that abnormal visits mainly occur in the second week before announcement dates.

-----Insert Table 2.12-----

Table 2.12 reports the regression analysis of the magnitude of earnings surprises on the number of visits. Earnings surprise (SUE) is calculated as the absolute value of actual earnings less the median of analyst forecasts reported in I/B/E/S, scaled by its stock price. We include only forecasts made for both the current and the next quarters. Our main variable of interest is the natural logarithm of the number of taxi visits (*Log Taxi*) that occur between the NYC firm and all NYC mutual funds.

Column 1 shows that the number of taxi trips that a firm has is negatively associated with earnings surprises. After controlling firm characteristics, we show in Column 2 that the coefficient on *Log Taxi* is still negative and significant and the magnitude is bigger. A one-standard-deviation increase in *Log Taxi* is associated with 18% drop in absolute SUE. In addition, we find that Log

MVE is also negatively related to SUE. The results are consistent with the intuition that more visits may result in a greater likelihood of information dissemination.

One may argue that *Log Taxi* may just capture the size effect on SUE because large firms by nature have less information asymmetry and more publicity. To alleviate this concern, we include an interaction term between *Log Taxi* and *Log MVE* in Column 3. The coefficients on *Log Taxi* and *Log MVE* are similar to the results in Column 2. Notably, the interaction term between *Log Taxi* and *Log MVE* is positive and significant at the 1% level. This suggests that, though in-house meetings reduce information asymmetry, the effect wanes as the firm becomes bigger. We include firm and year-quarter fixed effect in Column 4 and 5; the results are qualitatively similar. These results are consistent with Baik, Kang and Kim (2010), in which the authors find the informational advantage of local investors are stronger in firms with high information asymmetry, such as small firms, firms with high return volatility, and young firms.

2.4 Conclusion

Private interactions with corporate insiders are crucial for institutional investors to acquire proprietary information. In this study, we focus on one important yet unexplored information acquisition activity, in-house meetings, to investigate to what extent private interactions affect investors' portfolio choices. Since the publicly traded firms and institutional investors in the U.S. are not required to report their private communications, we use the taxi trips in New York City that occur between such institutions to proxy for in-house meetings. While on average NYC funds overweight NYC equities compared to non-NYC funds, we find that NYC funds that visit local firms more often exhibit greater overweighting. To the extent that fund managers obtain superior information through in-house meetings, we also find that the magnitude of overinvestment by NYC funds is more for the firms that they have visited than the ones that they have not visited.

As for the performance of the NYC positions of NYC funds, we find that NYC funds that have more local taxi trips outperform their non-NYC peers. Further, we show that the stocks that a fund purchases after meeting generate greater abnormal returns than the stocks that a fund purchases without meeting.

We also examine whether NYC funds could obtain earnings-related information through these private meetings. We find that fund managers tend to visit the firm before earnings announcement date rather than after. Specifically, the abnormal visits are concentrated in the second week before announcements. We show that the number of visits that a firm received is negatively associated with earnings surprises.

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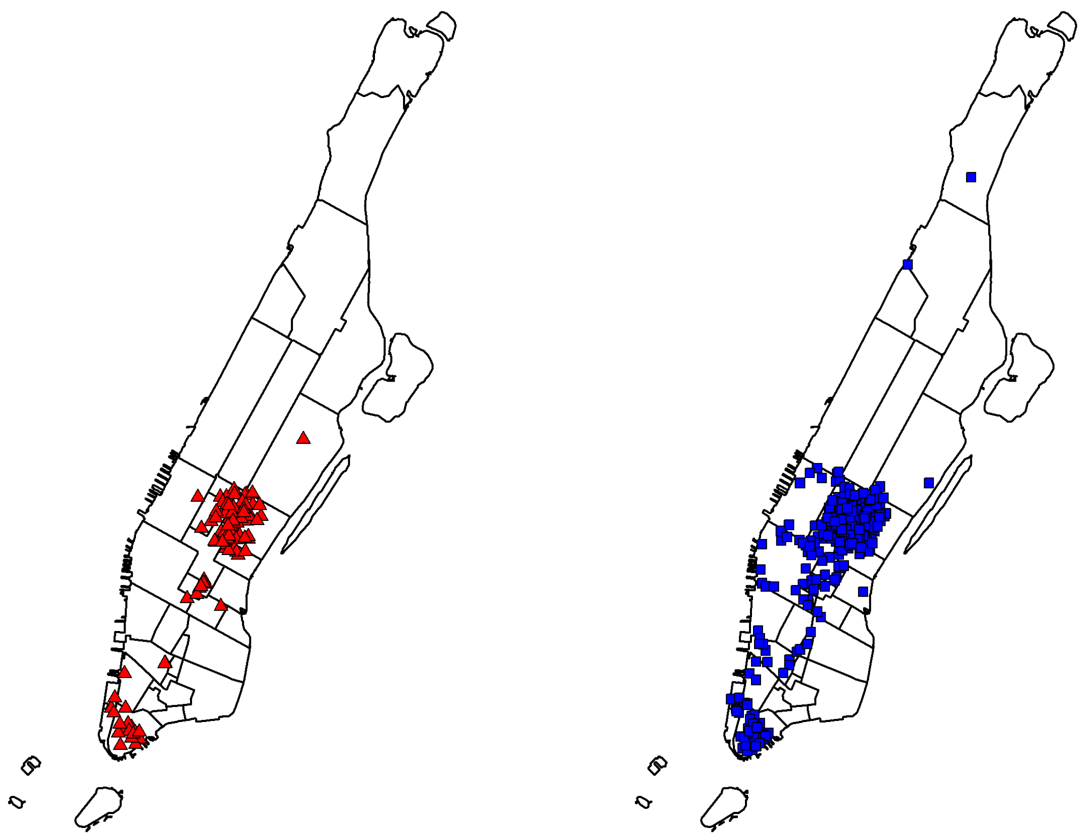
Figure 2.1
Locations of NYC Institutions

Panel A: NYC Funds　　　　Panel B: NYC Public Firms



Note: Panel A and B map the unique locations of NYC equity funds and NYC public firms from January 2009 to June 2016.

Table 2.1
Descriptive Statistics of NYC and non-NYC Funds

This table presents the summary statistics for U.S.-based equity funds. Our sample consists of 582 NYC funds and 2406 non-NYC funds from the first quarter in 2000 through the last quarter in 2017. We report the average total asset under management ($ million), the average number of holdings, the average number of holdings headquartered in NYC, and the average percentage of investment in NYC (%). In addition, we report the quarterly average taxi rides that occur between the NYC funds' managing office and all NYC public firms as well as the NYC firms that they hold. A taxi ride is included if both the pick-up location and the drop-off location are within the 30-meter radius of either a fund's office or a firm's headquarter. Multiple taxi rides to the same company are treated as one. The taxi ride data is available from January 2009 to June 2016.

	Mean	Median	SD	P25	P75
NYC Funds (582 Funds)					
Asset Under Management ($ million)	1097.20	371.40	2127.18	120.40	1102.40
Number of Holdings	89	65	76	44	101
Number of NYC Holdings	7	5	6	3	9
Fraction of NYC Holdings (%)	9.90	7.52	7.76	3.68	15.09
Taxi Trips to All NYC Firms	210	110	321	32	272
Taxi Trips to NYC Firms Held	12	6	17	2	14
Non-NYC Funds (2406 Funds)					
Asset Under Management ($ million)	1588.50	232.70	6475.97	66.10	941.00
Number of Holdings	88	69	68	47	102
Number of NYC Holdings	7	5	5	3	9
Fraction of NYC Holdings (%)	9.19	7.15	7.28	3.38	14.11

Table 2.2
Local Investments of NYC Funds and Non-NYC Funds

Panel A reports the average ownership in NYC firms of NYC and non-NYC funds. The sample consists of 582 NYC funds and 2406 non-NYC funds from the first quarter in 2000 through the last quarter in 2017. *NYC Market* is the percentage of the NYC stock market capitalization relative to the CRSP U.S. market capitalization. Panel B reports the NYC ownership after excluding index constituents, financial firms, and non-financial firms.

Panel A: NYC Bias by Year

Year	NYC Market (%)	NYC Funds (%)	Non-NYC Funds (%)	NYC – Non-NYC (%)	t-stat	p-val
2000	11.35	11.75	10.02	1.73	4.96	0.00
2001	13.13	12.30	11.30	1.00	2.75	0.01
2002	13.03	12.07	11.21	0.86	2.60	0.01
2003	12.38	12.33	11.52	0.81	2.44	0.01
2004	11.89	11.75	10.89	0.86	2.73	0.01
2005	10.80	10.54	9.85	0.69	2.45	0.01
2006	10.59	10.80	9.95	0.85	3.22	0.00
2007	10.13	10.28	9.56	0.72	2.80	0.01
2008	8.67	9.28	7.99	1.29	5.68	0.00
2009	7.94	8.95	7.79	1.16	5.15	0.00
2010	8.18	9.05	8.14	0.92	3.68	0.00
2011	8.16	8.61	8.19	0.41	1.74	0.08
2012	8.07	8.85	8.28	0.57	2.38	0.02
2013	8.55	9.13	8.47	0.67	2.56	0.01
2014	8.13	8.61	8.32	0.29	1.14	0.25
2015	7.88	8.36	8.31	0.04	0.16	0.88
2016	7.63	8.48	8.14	0.34	1.26	0.21
2017	7.45	8.23	7.82	0.41	1.51	0.13
2000-2017	9.66	9.90	9.19	0.71	10.77	0.00
2000-2008	11.33	11.06	10.18	0.88	8.88	0.00
2009-2017	8.00	8.71	8.16	0.55	6.55	0.00

Panel B: NYC Ownership in Non-index Constituents and Non-financial Stocks

	NYC funds	Non-NYC funds	NYC – Non-NYC
Exclude Dow 30	6.95	6.34	0.61***
Exclude S&P 100	4.14	3.66	0.48***
NYC Non-financials	5.48	4.88	0.60***
NYC Financials	4.57	4.36	0.21*

Table 2.3
NYC Bias and Fund Attributes

This table reports the average NYC investments for various types of funds. The sample consists of 582 NYC funds and 2406 non-NYC funds from the first quarter in 2000 through the last quarter in 2017. We divide funds into quintiles based on total net assets, number of holdings, and age, and report the average NYC investments of NYC funds and non-NYC funds. Panel A and panel B show the results for the periods 2000-2008 and 2009-2017, respectively.

Panel A: 2000-2008

	NYC Funds	Non-NYC Funds	NYC – Non-NYC	t-stat
		Fund Size		
Q1 (Small)	9.52	8.91	0.61**	2.43
Q2 - Q5	10.95	9.90	1.05***	8.39
Q5 (Large)	12.66	12.40	0.26	1.11
		Number of Holdings		
Q1 (Undiversified)	13.93	11.71	2.22***	8.19
Q2 - Q5	11.07	10.25	0.82***	6.49
Q5 (Diversified)	8.52	8.45	0.07	0.39
		Fund Age		
Q1 (Young)	11.29	9.56	1.72***	6.94
Q2 - Q5	9.99	9.84	0.15	1.21
Q5 (Old)	13.79	11.96	1.83***	8.22

Panel B: 2009-2017

	NYC Funds	Non-NYC Funds	NYC – Non-NYC	t-stat
		Fund Size		
Q1 (Small)	8.25	7.42	0.83***	3.50
Q2 - Q5	8.72	8.04	0.68***	6.46
Q5 (Large)	8.94	9.31	-0.37**	-2.00
		Number of Holdings		
Q1 (Undiversified)	10.17	9.06	1.11***	4.53
Q2 - Q5	9.11	8.06	1.06***	9.90
Q5 (Diversified)	5.99	7.52	-1.53***	-11.67
		Fund Age		
Q1 (Young)	9.31	7.72	1.59***	5.98
Q2 - Q5	8.11	8.01	0.11	1.08
Q5 (Old)	10.00	9.12	0.88***	4.51

Table 2.4
NYC Bias by Taxi Rides and Other Fund Characteristics

This table shows the average NYC bias of NYC funds sorted on different characteristics from January 2009 to June 2016. We calculate the NYC bias for fund i at the end of quarter t as follows:

$$NYC\ Bias_{i,t} = \sum_{k=1}^{K} w_{i,t}^{k} - \frac{\sum_{j}^{J} \sum_{k=1}^{K} w_{j,t}^{k}}{J}$$

where K is the set of stocks that are held by at least one mutual fund and are located in NYC, and I and J are the set of NYC and non-NYC mutual funds in the same Lipper Class. $w_{i,t}^{k}$ and $w_{j,t}^{k}$ are the portfolio weights applied to fund i and j's NYC holdings. We compute the quarterly number of taxi trips between a NYC fund and all NYC public firms and define a fund as ”busy” if its number of trips is greater than median and ”unbusy” if otherwise. A taxi ride is included if both the pick-up location and the drop-off location are within the 30-meter radius of either a fund's office or a firm's headquarter. “Busy” and “unbusy” funds are further sorted into halves based on total net assets, number of holdings, and age.

	INF Funds	LINF Funds	Difference	t-stat
		Panel A: Taxi Rides		
NYC Bias	0.80	0.41	0.40***	2.89
		Panel B: Fund Size		
Small Funds	0.93	0.25	0.68***	3.16
Large Funds	0.65	0.56	0.09	0.66
		Panel C: Number of Holdings		
Undiversified Funds	1.15	0.67	0.48**	2.50
Diversified Funds	0.45	0.16	0.30*	1.92
		Panel D: Fund Age		
Old Funds	1.02	0.44	0.58***	4.26
Young Funds	0.39	0.35	0.04	0.23

Table 2.5
Hyper Bias and Distance Buckets

This table examines the fund's NYC bias in firms at different distances from January 2009 to June 2016. We divide funds' NYC holdings into hyper-local and local-distant portfolios based on the fund-firm distance using 0.5 miles or 0.75 miles as the breakpoint. We compute NYC bias in each distance bucket as the difference between the fraction of fund assets in stocks in a distance bucket and the fraction of the market capitalization that resides in the same distance bucket. We compute the quarterly number of taxi trips between a NYC fund and all NYC public firms and define a fund as ”busy” if its number of trips is greater than median and ”unbusy” if otherwise. Panel A reports the results with all NYC firms. Panel B reports the results with NYC firms that are not Dow 30 constituents. t-stats are in parentheses.

		"Busy" Funds	"Unbusy" Funds	"Busy" – "Unbusy"
Panel A: All NYC Stocks				
0.5-mile Radius	⩽ 0.5 Miles	0.12	0.09	0.02
		(1.28)	(1.63)	(0.22)
	> 0.5 Miles	0.08	0.40***	-0.32**
		(0.90)	(4.04)	(-2.36)
0.75-mile Radius	⩽ 0.75 Miles	0.12	0.16*	-0.04
		(1.26)	(2.04)	(-0.26)
	> 0.75 Miles	0.08	0.33***	-0.26**
		(1.06)	(3.75)	(-2.25)
Panel B: Excluding Dow 30 Constituents				
0.5-mile Radius	⩽ 0.5 Miles	0.25***	0.19***	0.05
		(2.79)	(3.94)	(0.53)
	> 0.5 Miles	0.69***	0.49***	0.20*
		(9.62)	(6.18)	(1.88)
0.75-mile Radius	⩽ 0.75 Miles	0.32***	0.32***	0.00
		(3.35)	(5.41)	(0.00)
	> 0.75 Miles	0.62***	0.37***	0.25**
		(10.81)	(4.59)	(2.58)

Table 2.6
NYC Bias and the Frequency of Taxi Trips

This table compares the local bias of NYC funds in firms that they visit and that they do not visit. For each NYC fund, we split its NYC holdings into two portfolios, "taxi trips" and "no trips" based on the number of taxi trips to each firm. We further divide the "taxi trips" portfolio into two subgroups, "one trip" and "multiple trips." NYC bias at the fund-stock level is calculated as the difference in the NYC investments between NYC funds and non-NYC funds in the same Lipper class. We then sum up the stock level biases to get the local bias for each fund's "taxi trips" and "no trips" portfolios. Panel A reports the results for all NYC funds; panel B, C, and D report the results for subsets of NYC funds formed on total net assets, number of holdings, and fund age. t-statistics are in parentheses.

	Taxi Trips V.S. No Trips			Multiple Trips V.S. One Trip		
	(a) Taxi Trips	(b) No Trip	(a) - (b)	(c) Multiple Trips	(d) One Trip	(c) – (d)
Panel A: All NYC Funds						
NYC Bias	2.31	1.85	0.46	1.37	0.94	0.43
	(54.73)	(50.28)	(9.41)	(44.74)	(41.77)	(12.84)
Panel B: Fund Size						
Large Funds	1.95	1.93	0.02	1.13	0.82	0.30
	(34.67)	(36.76)	(0.24)	(22.32)	(26.91)	(4.9)
Small Funds	2.63	1.79	0.84	1.58	1.05	0.52
	(28.43)	(42.45)	(7.46)	(19.95)	(24.77)	(6.02)
Panel C: Number of Holdings						
Diversified Funds	0.97	0.78	0.19	0.56	0.41	0.14
	(18.43)	(26.88)	(3.5)	(13.82)	(16.28)	(3.38)
Undiversified Funds	3.61	2.93	0.68	2.14	1.46	0.68
	(38.76)	(40.24)	(4.4)	(23.7)	(29)	(6.03)
Panel D: Fund Age						
Old Funds	2.10	1.88	0.21	1.24	0.86	0.38
	(35.17)	(42.58)	(2.26)	(21.8)	(27.67)	(5.46)
Young Funds	2.49	1.83	0.65	1.47	1.02	0.45
	(30.23)	(50.24)	(6.27)	(20.44)	(29.22)	(5.79)

Table 2.7
Performance of NYC Positions

This table compares the performance on NYC positions of NYC funds versus non-NYC funds, as well as diligent funds versus lazy funds. The sample consists of 582 NYC funds and 2406 non-NYC funds from the first quarter in 2000 through the last quarter in 2017. The dependent variable is the monthly value-weighted return of a fund's NYC positions in excess of the one-month Treasury bill rate. NYC Fund Dummy equals one if a fund's managing office is located in New York City. "Busy" ("Unbusy") NYC Fund equals one if an NYC fund has more (fewer) than median taxi rides to all NYC public firms in the previous quarter. A taxi ride is included if both the pick-up location and the drop-off location are within the 30-meter radius of either a fund's office or a firm's headquarter. The taxi ride data is available from January 2009 to June 2016. We control for the Fama-French-Carhart factors, total net assets, number of holdings, and age. We include Year-quarter and Lipper class fixed effects. Standard errors (clustered by fund) are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
NYC Fund Dummy	0.05**		0.05**		
	(0.02)		(0.02)		
"Busy" Fund		0.09**		0.09**	0.09**
		(0.04)		(0.04)	(0.04)
"Unbusy" Fund		-0.06		-0.06	-0.06
		(0.05)		(0.05)	(0.05)
R_M - R_f (%)	1.05***	1.08***	1.03***	1.04***	1.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
SMB (%)			0.09***	0.12***	0.12***
			(0.01)	(0.01)	(0.01)
HML (%)			0.25***	0.14***	0.14***
			(0.01)	(0.01)	(0.01)
UMD (%)			-0.01**	0.03***	0.03***
			(0.00)	(0.00)	(0.00)
Log (Fund Assets)					-0.00
					(0.01)
Log (# Holdings)					0.14***
					(0.02)
Age					-0.00
					(0.00)
Constant	0.21	0.58***	0.05	0.81***	0.24*
	(0.14)	(0.09)	(0.14)	(0.10)	(0.14)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Lipper FE	Yes	Yes	Yes	Yes	Yes
# of Obs	273,406	113,687	273,406	113,687	113,687
Adj. R-squared	0.4770	0.5166	0.4847	0.5194	0.5195

Table 2.8

Performance of NYC Positions (Return Difference as Independent Variable)

This table compares the excess returns on NYC positions of NYC funds versus non-NYC funds, as well as diligent funds versus lazy funds. The sample consists of 582 NYC funds and 2406 non-NYC funds from the first quarter in 2000 through the last quarter in 2017. The dependent variable is return difference between a fund's NYC positions and its non-NYC positions. NYC Fund Dummy equals one if a fund's managing office is located in New York City. "Busy" ("Unbusy") Fund equals one if an NYC fund has more (fewer) than median taxi rides to NYC public firms in the previous quarter. A taxi ride is included if both the pick-up location and the drop-off location are within the 30-meter radius of either a fund's office or a firm's headquarter. The taxi ride data is available from January 2009 to June 2016. We control for the Fama-French-Carhart factors, total net assets, number of holdings, and age. We include Year-quarter and Lipper class fixed effects. Standard errors (clustered by fund) are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
NYC Fund Dummy	0.05**		0.05**		
	(0.03)		(0.03)		
"Busy" Fund		0.12***		0.12***	0.12***
		(0.04)		(0.04)	(0.04)
"Unbusy" Fund		-0.05		-0.05	-0.05
		(0.05)		(0.05)	(0.05)
R_M - R_f (%)	-0.02**	0.01	0.00	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
SMB (%)			-0.15***	-0.17***	-0.17***
			(0.01)	(0.01)	(0.01)
HML (%)			0.23***	0.21***	0.21***
			(0.01)	(0.01)	(0.01)
UMD (%)			-0.03***	0.02***	0.02***
			(0.00)	(0.01)	(0.01)
Log (Fund Assets)					-0.01
					(0.01)
Log (# Holdings)					0.13***
					(0.02)
Age					-0.00
					(0.00)
Constant	-1.11***	0.90***	-1.05***	1.24***	0.75***
	(0.15)	(0.10)	(0.15)	(0.10)	(0.14)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Lipper FE	Yes	Yes	Yes	Yes	Yes
# of Obs	273,406	113,687	273,406	113,687	113,687
Adj. R-squared	0.0292	0.0183	0.0442	0.0274	0.0277

Table 2.9

Performance of Transaction-Based Portfolios

This table presents the regression analysis of portfolios formed on fund trades and taxi rides between fund and firm in the previous quarter. For each fund, we form two portfolios based on their trades, namely a "BUY" portfolio and a "SELL" portfolio. We further divide each portfolio into "in-house meetings" and "no meetings" based on the number of taxi trips. The dependent variable in column 1 to 3 is the monthly return difference between the "visited and buy" and "not visited and buy" portfolios. The dependent variable in column 4 to 6 is the monthly return difference between the "visited and sell" and "not visited and sell" portfolios. We include time and fund fixed effects. Standard errors (clustered by fund) are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	BUY Portfolio $R_{\#\ Meetings > 0} - R_{\#\ Meetings = 0}$			SELL Portfolio $R_{\#\ Meetings > 0} - R_{\#\ Meetings = 0}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	4.57***	4.23***	1.66**	0.27	-0.52	-0.66
	(0.85)	(0.83)	(0.82)	(0.73)	(0.75)	(0.72)
R_M - R_f (%)		0.07*	-0.03		0.16***	0.15***
		(0.04)	(0.04)		(0.03)	(0.03)
SMB (%)			0.10*			-0.02
			(0.06)			(0.06)
HML (%)			0.00			0.14**
			(0.07)			(0.07)
UMD (%)			-0.21***			0.07
			(0.04)			(0.05)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs	7022	7022	7022	6253	6253	6253
Adj. R-squared	0.0072	0.0076	0.0179	0.0214	0.0254	0.0260

Table 2.10
Stock Returns and Trades of NYC Mutual Fund Investors

This table reports the regression analysis of stock returns on the changes in the ownership of NYC mutual fund investors. The dependent variable is the monthly excess return, $R_{i,t}$ - $R_{f,\,t}$. For every firm quarter, we divide a firm's mutual fund investors into funds that have visited the firm and funds that have not based on the taxi rides in the previous quarter between fund and firm. We compute the quarterly trades made by each type of mutual funds as:

$$Trade_{i,t}^{T} = \log(2 + \frac{\sum_{j=1}^{J} \Delta Shares_{j,t}^{T}}{\sum_{j=1}^{J} Shares_{j,t-1}^{T}}), \text{ and}$$

$$Trade_{i,t}^{NT} = \log(2 + \frac{\sum_{j=1}^{J} \Delta Shares_{j,t}^{NT}}{\sum_{j=1}^{J} Shares_{j,t-1}^{NT}}),$$

where i and j denote firm and fund respectively. *T* and *NT* indicate whether or not the fund has taxi trips to the firm. A taxi ride is included if both the pick-up location and the drop-off location are within the 30-meter radius of either a fund's office or a firm's headquarter. The taxi ride data is available from January 2009 to June 2016. Standard are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
$Trade^{T}$	0.23*		0.30**	
	(0.13)		(0.14)	
$Trade^{NT}$		-0.27**	-0.16	
		(0.12)	(0.13)	
$Trade^{T} - Trade^{NT}$				0.22***
				(0.08)
R_M - R_f (%)	1.10***	1.10***	1.12***	1.12***
	(0.03)	(0.03)	(0.03)	(0.03)
SMB (%)	0.39***	0.39***	0.27***	0.27***
	(0.04)	(0.04)	(0.04)	(0.04)
HML (%)	0.16***	0.14***	0.21***	0.21***
	(0.05)	(0.05)	(0.05)	(0.05)
UMD (%)	-0.01	0.04	0.06*	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)
Constant	-0.33**	0.04	-0.14	-0.02
	(0.14)	(0.14)	(0.21)	(0.10)
# of Obs	8007	7621	5931	5931
Adj. R-squared	0.2696	0.2746	0.3065	0.3066

Table 2.11
Timing of Taxi Trips

This table reports the coefficient estimates from the OLS regression of the number of taxi trips over a time window around the earnings announcement date on various time window dummies. Setting the earnings announcement date as day t, we include only taxi trips that occur between t-30 to t+30. The dependent variables in Column (1) and (2), (3) and (4), and (5) and (6) are the natural logarithm of the number of taxi trips that a firm has over one-month, two-week, and one-week window, respectively, around the earnings announcement date. Month -1 dummy equals one if the time window is from day t-30 to day t-1 and zero if from day t+1 to day t+30. Week -2 to -1 dummy indicates the time window of t-14 to t-1. Week -4 to -3 dummy indicates the time window of t-28 to t-15. Week -1 dummy indicates the time window of t-7 to t-1. Week -2 dummy indicates the time window of t-14 to t-8. Week -3 dummy indicates the time window of t-21 to t-15. Week -4 dummy indicates the time window of t-28 to t-22. We control for firm size (Log MVE), book-to-market ratio (BM Ratio), sales growth (Sales Growth), leverage ratio (Leverage), earnings per share scaled by price (EP Ratio), the change in net income (△Earn), analyst following (Log # Analyst). All control variables are lagged by one quarter. We exclude Saturday and Sunday from the sample. Standard errors are clustered by calendar quarter.

	(1)	(2)	(3)	(4)	(5)	(6)
Month -1	0.0404***	0.0408***				
	(0.0140)	(0.0141)				
Week -2 to -1			0.0482***	0.0487***		
			(0.0174)	(0.0175)		
Week -4 to -3			0.0101	0.0104		
			(0.0149)	(0.0150)		
Week -1					0.0236	0.0240
					(0.0150)	(0.0150)
Week -2					0.0596***	0.0599***
					(0.0183)	(0.0184)
Week -3					0.0105	0.0108
					(0.0160)	(0.0161)
Week -4					0.0088	0.0091
					(0.0176)	(0.0177)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes
Year-Quarter FE	No	Yes	No	Yes	No	Yes
N	8224	8224	12336	12336	20560	20560
adj. R-sq	0.0019	0.7727	0.0012	0.7334	0.0006	0.6477

Table 2.12
Earnings Surprise and Taxi Trips

This table reports the regression results of quarterly standardized unexpected earnings (SUE) on the number of taxi visits in the previous quarter. The dependent variable is the absolute value of SUE. SUE is calculated as the absolute value of actual earnings less the median of analyst forecasts reported in I/B/E/S, scaled by its stock price. We include only forecasts made for both the current and the next quarters. *Log Taxi* is the natural logarithm of the number of taxi visits that occur between the NYC firm and all NYC mutual funds. *Log MVE* is the natural logarithm of the market value of the NYC firm. *BM Ratio* is the ratio of the firm's book value to market value of assets. *Sales Growth* is the percentage change in sales from the previous quarter. *Leverage* is the ration of the firm's total debt to total assets. *Earning-price Ratio* is earnings per share scaled by stock price. *ΔEarn* is the change in net income from the previous quarter scaled by total assets. *Log # Ana*lyst is the natural logarithm of the number of analysts following the firm. All independent variables are lagged by one quarter. Standard errors (clustered by quarter) are in parentheses.

	(1)	(2)	(3)	(4)	(5)
Log Taxi	-0.0008**	-0.0011***	-0.0142***	-0.0153***	-0.0241*
	(0.0004)	(0.0004)	(0.0046)	(0.0045)	(0.0141)
Log MVE		-0.0015**	-0.0054***	-0.0053***	-0.0124**
		(0.0006)	(0.0016)	(0.0017)	(0.0054)
Log ride * Log MVE			0.0006***	0.0006***	0.0010
			(0.0002)	(0.0002)	(0.0006)
BM Ratio		0.0051**	0.0051**	0.0048**	0.0022
		(0.0021)	(0.0021)	(0.0021)	(0.0050)
Sales Growth		0.0009	0.0009	0.0012*	0.0006
		(0.0007)	(0.0007)	(0.0006)	(0.0007)
Leverage		0.0155***	0.0151***	0.0149***	0.0221*
		(0.0033)	(0.0033)	(0.0032)	(0.0122)
Earning-price Ratio		-0.0071	-0.0066	-0.0054	-0.0054
		(0.0082)	(0.0080)	(0.0084)	(0.0057)
ΔEarn		0.0074	0.0075	0.0058	0.0042
		(0.0074)	(0.0077)	(0.0074)	(0.0048)
Log # Analyst		-0.0017	-0.0016	-0.0022	-0.0022
		(0.0015)	(0.0015)	(0.0019)	(0.0025)
Constant	0.0128***	0.0425***	0.1300***	0.1374***	0.2996**
	(0.0031)	(0.0113)	(0.0355)	(0.0353)	(0.1222)
Firm FE					Yes
Year-Quarter FE				Yes	Yes
N	3371	3371	3371	3371	3371
adj. R-sq	0.0011	0.0293	0.0316	0.0372	0.0983

Chapter 3
Natural Disasters: "Good or Bad" for Banks?

3.1 Introduction

Natural disasters are exogenous and negative shocks to the communities in which they occur.[5] Unfortunately, such disasters are not rare and costless events. Indeed, according to Boustan et al. (2019), "[t]hrough most of the century, the US experienced around 500 county-level disaster events each year." More alarmingly, "[s]ince the early 1990s, there has been a clear acceleration in disaster counts, reaching around 1,500 county-level events per year by the 2000s." Furthermore, according to Deryugina (2017), "...real disaster costs are high and growing faster than GDP…." A major concern is that disasters like hurricanes, tornados, floods, wildfires, and earthquakes can cause severe property damage, including damages to homes, businesses, and automobiles. Over the years various efforts have been undertaken to mitigate the adverse effects of natural disasters, but not surprisingly, given their unpredictability and severity, without complete success. As individuals and business owners take actions to repair the damage, many will obtain funding from private insurance policies covering such damages and disaster relief from state and federal agencies. However, these funds typically do not cover the full amount of damages. This requires individuals and business owners to seek funds from other sources.

Given that one long-standing and important source of funding for individuals and firms for a variety of purposes is banks, we examine the impact of natural disasters on both banks and their

[5] The exogeneity of some natural disasters may be subject to dispute in the long run. In particular, some may argue that human actions can contribute to future disasters due to their effect on, for example, deforestation and global warming. However, in the short run, this is unlikely to be the case for the types of natural disasters considered here.

branches.[6] Individuals and business owners can withdraw deposits and apply for loans at banks to obtain additional funding for reconstruction efforts. In this way, banks can play an important supporting role in the positive response to the negative impact of large shocks to local communities.[7] More specifically, disasters generally lead to an increase in the demand for loans from banks/branches located in the communities where disasters strike and they respond by raising deposit rates to attract additional funding to provide the higher lending in those markets.[8]

Although clearly quite important, the literature on the impact of natural disasters on banks is relatively sparse. One of the earliest papers is by Steindl and Weinrobe (1983), whose focus is quite narrow in that they only examine what happens to the deposits of banks following a natural disaster. They find that runs on the banks in their sample did not occur and, in most cases, the banks actually experienced a significant increase in deposits following four sizeable disasters. More recently, Dlugosz et al. (2018) also examine the deposit experience of banks but focus on whether branches of banks in communities affected by natural disasters can set deposit rates locally and thereby be in a position to raise those rates to attract additional deposits to meet the increase in loan demand for the reconstruction that takes place. They find that branches that set rates locally do increase deposit rates more and experience higher deposit volumes in counties affected by natural disasters. This paper provides a reason for Steindal and Weinrobe's (1983) finding that

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[6] Other studies examine the impact of natural disasters on different outcomes. For example, Cavallo et al. (2013) examine the direction and magnitude of the average casusal effect of large natural disasters on economic growth and Anttila-Hughes and Hsiang (2013) examine the post-disaster economic and health effects of typhoons. Also, Berg and Schrader (2012) examine the impact of volcanic erruptions on an Ecudorian microfinance institution and find that credit demand increases, but access to credit is restricted.

[7] The Federal Deposit Insurance Corporation (FDIC) issues Financial Institution Letters in response to various natural disasters that strike different parts of the country over time in which the general message is that banks in the affected areas are encouraged to meet the financial services needs on their communities.

[8] See Cortes (2017) for a nice discussion of the response of banks as outlined here to natural disasters that strike local communities.

deposits increase following natural disasters -- deposit rates are increased to satisfy an increased loan demand, something not explored by them.

Focusing more on the impact of natural disasters on bank lending, an important and recent study is by Cortes and Strahan (2017). They find that bank lending, in the form of home mortgage originations, increases significantly during the months following disasters as residents in the affected communities rebuild destroyed or damaged physical capital. Importantly, they interpret their results as suggesting financially integrated banks, those banks with more geographically located branches, can reallocate funds toward markets with high credit demand, such as the counties where natural disasters occur, and away from other markets in which they hve branches. The results do not apply to banks of all sizes but are found to be driven by small banks, those with assets less than $2 billion. Also, they find that banks exposed to natural disasters bid up deposit rates to help fund the unexpected high loan demand in the shocked communities. Interestingly, despite the high loan demand they do not find any effect on mortgage loan rates. In an earlier paper, Cortes (2014) finds that loan growth rates at truly local lenders, those lenders with more than 65% of their deposits in the market, increase in the event of natural disasters. As a result, he finds that the additional funding leads to higher employment growth at either young or small firms. In a related study, Koetter, Noth, and Rehbein (2019) study the response of banks to the flooding of river Elbe in Germany that severely adversely affected counties around the river in May 2013. They find that local banks in unaffected counties but exposed to “disaster-ridden” firms in affected counties lend 3 percent more in the post-flood period compared with unexposed local banks. In addition, they find this expansion in lending is not associated with higher insolvency risk, higher loan impairment rates, or with rent-skimming from (disaster-) captured, small firms. In another recent paper, He (2018) examines the impact of natural disasters on borrowers with strong relationships with banks. In this case, she finds that such borrowers receive more loans after natural disasters. At the same time, connected borrowers who are not affected by natural disasters suffer substantial loan declines, output losses, and declines in equity values. Unlike the Cortes and Strahan (2017), the latter three papers to not connect the deposit-side of a bank's balance sheet to the asset side.

In general, and as discussed, the relatively few studies of the impact of natural disasters on banks and/or bank branches focus on the response of banks in terms of their deposits and loans. Yet, none of the studies focus on the overall performance of banks located in communities exposed to natural disasters.[9] Nor do the studies ling the response of the branches of banks to the overall bank performance. One exception, however, is the paper by Klomp (2014), who studies the impact of natural disasters on the likelihood of a bank's default. He does this based on the examination of 170 large-scale natural disasters over 160 countries over the period 1997-2010. His empirical results indicate that "… although large-scale natural disasters increase financial fragility, natural catastrophes cannot explain the occurrence of a domestic banking crisis." Similar to Klomp (2014), we study the impact of natural disasters on overall bank performance. However, we do so in the context of a single country, namely the U.S., with counties rather than countries as the geographical units of observation, and choose to not focus on a bank's likelihood of failing, as measured by a z-score.

As a result, our contribution to the limited research on natural disasters and banks is threefold. First, we appear to be the first to examine the impact of natural disasters on a bank's overall performance as measured by return on assets and net interest margin. As already noted,

[9] One paper by Schüwer et al. (2019) do examine the impacts of Hurricane Katrina, Rita and Wilma on the asset quality of the banks in the affected areas and find that profitability is adversely affected. However, this study is more limited in scope than our study in that it focuses on 135 counties in the Gulf Coast region for the second half of 2005.

other studies indicate that deposit rates and loan rates increase after natural disasters. It, therefore, follows that if loan rates increase more than deposit rates, net interest margin should increase, which in turn should likely lead to an increase in return on assets. We find that indeed the net interest margin and the return on assets increase for banks more exposed to natural disasters. Second, we appear to be the first to find that the impact of natural disasters on deposit and loan rates set by the branches of banks is higher rates on both, but with loan rates increasing more than deposit rates. This finding is consistent with our finding of an increase in net interest margin, and thereby return on assets, due to the exogenous shocks caused by natural disasters. Third, we appear to be the first to find that brokered deposits are a way in which banks/branches located in communities hit by disasters can obtain additional deposits apart from obtaining more local deposits by setting higher interest rates or by shifting deposits from branches outside the affected communities. Our threefold contribution essentially tries to tie together the papers discussed above by identifying the channels through which banks can respond to natural disasters and thereby ultimately affect their overall performance.

The remainder of the paper proceeds as follows. In the next section, the data used in our paper is presented and discussed. The model used to analyze the impact of natural disasters on our measures of bank performance, funding by banks, and deposit and loan rates are also presented in the section. In Section 3.3, the empirical results are presented and discussed. The paper concludes with a summary in Section 3.4.

3.2 Data and Model

3.2.1 Data

There are three main data sources for our study. The first is information on natural disasters, which we obtain from the Spatial Hazard Event Loss for the United States (SHELDUS) dataset. It is a monthly, county-level dataset that covers natural disasters such as thunderstorms, hurricanes, floods, wildfires, and tornados as well as perils such as flash floods, heavy rainfall. The database contains information on the date of an event, affected location (county and state) and the direct property losses caused by the event from 1960 to present. [10]

Figure 3.1 shows the property damages caused by natural disasters in counties throughout the U.S. over the period 2000 to 2017. Clearly, the magnitude of the impact of the disasters has largely been focused on the coastal counties. This may be seen by the darkest shading in the map. The total damages over the period are $406 billion due to 1,007 Presidential Disaster Declarations (PDD).[11] Of course, the number of PDDs can include more than one county. Indeed over the entire period there are counties in which there were a total of 10,051 natural disasters. This means that some counties experienced more than one disaster.

-----Insert Figure 3.1-----

Figure 3.2 shows the percentage of the 2,233 counties that suffered from natural disasters for each of the years 2000 to 2017. The percentages range from a high of 31 percent in 2005, which involved 993 counties, to a low of 6 percent in 2014, which involved 204 counties (also see Table 3.A1). It is important to point out that some counties experience more than one natural disaster over the period.

-----Insert Figure 3.2-----

[10] SHELDUS™ was developed by the Hazards and Vulnerability Research Institute at the University of South Carolina and originally supported by grants from the National Science Foundation (Grant No. 99053252 and 0220712) and the University of South Carolina's Office of the Vice President for Research. Since 2018, the ASU Center for Emergency Management and Homeland Security supports and maintains SHELDUS™.

[11] The Department of Homeland Security and its Federal Emergency Management Agency (FEMA) administer disaster assistance and emergency management in the U.S. State governors initiate requests for disaster assistance. If the President finds that a major disaster or emergency exists, FEMA activates Federal funding programs to assist in the response and recovery effort.

In terms of counties suffering the largest property damages from natural disasters, Figure 3.3 shows that the top 25 counties account for $233 billion of the $406 billion in total damages, or 57 percent, over the entire period 2000-2017. The 25 counties, moreover, are located in 8 states, with all but one county located near coastal regions. The county experiencing the largest property damages was Monmouth in New Jersey, at $26 billion. The county experiencing the smallest property damages was Miami-Dade in Florida, at $3.5 billion. (Table 3.A2 provides information on the number of banks and bank branches in these counties. It shows that the number of bank headquarters in these 25 counties ranges from a low of 0 to a high of 59, while the number of offices ranges from a low of 8 to a high of 2,798.)

Although not shown in a figure, information on the top 25 counties ranked by the highest single damages within the eighteen years is provided in Table 3.A3. There is substantial overlap between the information in Figure 3.3 (Table 3.A2) and Table 3.A3. In particular, 23 of the 25 top counties are included when rank by both the highest total damages and the highest single damages. The differences in the damages are mainly due to multiple disasters in some counties over the entire period 2000 to 2017. There is also a difference in the number of banks and bank branches in Tables 3.A2 and A3 because the former table covers eighteen years, while the latter table covers a single month and year.

-----Insert Figure 3.3-----

We also need information on both banks and bank branches for our study, which we obtain from two sources. The information on the number of branches held by each bank in each county-year is obtained from the Summary of Deposits from the Federal Insurance Deposit Corporation

(FDIC). The bank control variables included in our empirical model are obtained from the Call Reports from the FDIC.

Figure 3.4 shows the number of banks and their branches in counties throughout the U.S. over the period 2000 to 2017. It should be noted that the number of banks declined to 5,797 in 2017 from 10,119 in 2000, a reduction of 43 percent. At the same time, the number of offices, which includes bank headquarters and their branches, was 85,492 in 2000 and increased to a high of 99,550 in 2009, before declining to 89,857 in 2017. As the figure indicates, there are banks and branches located in almost all of the 3,233 counties in the U.S. Over the entire period, there are as few as 23 counties (in 2004) and as many as 35 counties (in both 2016 and 2017) without either banks or branches. However, there is a difference between the number of locations for bank headquarters and bank branches, as indicated above. In particular, there were 567 counties in 2000 without any bank headquarters, while the number of such counties increased to 1,012 in 2017 (see Table 3.A1).

-----Insert Figure 3.4-----

Figure 3.5 shows the percentage of counties with both natural disasters and banks and/or branches. Over the period, there was a low of 204 counties with natural disasters in 2014 and a high of 993 counties in 2005.[12] The figure shows that almost all the counties suffering natural disasters had either bank headquarters or branches of the banks located in them. In terms of branches, the percentage of such counties with branches located in them was at least 99 percent. In terms of bank headquarters, however, the percentage of bank headquarters located in such

[12] In 2005, Hurricane Katrina struck the southeastern U.S. and created damages in many counties in the states of Florida, Alabama, Louisiana and Mississippi.

counties ranges from a low of 70 percent in 2016 to a high of 91 percent in 2001 (also see Table 3.A1).

-----Insert Figure 3.5-----

Figure 3.6 shows the states in which the top 25 banks are headquartered and the total property damages that they suffered from the natural disasters, including both the total property damages and the number of disasters, over the period 2000 to 2017. The total damages incurred by these banks is $125 billion, or 31 percent of the total damages over the entire period. Interestingly, these 25 banks were headquartered in counties that were collectively exposed to 183 natural disasters. As may be seen, Woodforest National Bank in Texas suffered the most damages, at $14 billion, and was exposed to 4 disasters. The bank that was exposed to the most disasters was Bridge City State Bank in Texas, at 13 (also see Table 3.A4). Information on the top 25 banks and the top 25 bank headquarters and bank branches, ranked by the highest single damages within the eighteen-year period is provided in Tables 3.A5 and 3.A6, respectively. The main differences in Tables 3.A4 and Tables 3.A5 and 3.A6 is due to the former only focusing on total damages for bank headquarters and the latter focusing on single damages for both bank headquarters and their branches.

-----Insert Figure 3.6-----

An additional dataset we use is obtained from RateWatch. This firm, established in 1989, collects information on various deposit and loan rates for bank locations throughout the U.S. every week. In particular, this dataset enables us to determine the response of banks to natural disasters in terms of the deposit and loan rates set at the branch level in both counties experiencing natural disasters and those not experiencing them.

3.2.2 Model

The basic model that we estimate is as follows:

$$\text{Outcome Variable}_{i,j,t} = \alpha_{i,t} + \sum_{k=1}^{4} \beta_k \text{Disaster Exposure}_{i,t-k} + \text{Control Variables}_{i,t} + \varepsilon_{i,j,t}, \dots \dots (1)$$

where i represents banks/branches, j represents counties, t represents time, and k represents lags of the disaster exposure variable. The outcome variables based on the quarterly data (k=1 to 4) for the overall bank are return on assets (ROA), net interest margin and brokered deposits. The outcome variables based on monthly data (k=1 to 12) are deposit and loan rates.

The main variable of interest is disaster exposure. In this case, we follow Cortes and Strahan (2017) and measure it as follows:

$$\text{Disaster Exposure}_{i,t} = \ln\left(\sum_{j=1}^{n} \text{Property Damage in Shocked Counties}_{j,t} * \text{Bank Share}_{i,j,t-1}\right)/N_{i,t} \quad (2)$$

where i represents banks, j represents counties, and t represents quarters for bank headquarter-level data or months for branch-level data. Branch $\text{Share}_{i,j,t-1}$ equals the number of branches owned by bank i in county j, divided by the total number of bank branches in county j. $N_{i,t}$ represents number of bank branches for bank i at time t.

In our analysis we are comparing counties affected by natural disasters and those unaffected by natural disasters in the same country so that any aggregate impacts of natural disasters are held constant. Importantly, we can estimate the causal effect of natural disasters on bank performance, bank funding, and deposit and loan rates as long as nothing is changing in the affected and non-affected banks following natural disasters that is not caused by them.

3.3 Empirical Results

The variables, and their summary statistics, used in our regression equations are provided in Table 3.1. Information for both the disaster exposure and bank-level variables on a quarterly basis is provided in Panel A, while deposit and loan rates at the branch level on a monthly basis are provided in Panel B. As may be seen in the table, there is substantial variation in the values of the variables in both panels. This is evidenced by the substantial difference in the minimum and maximum value of the variables. In particular, notice that one bank has 6,765 branches, while another bank has no branches. Also, notice that at least one bank pays no interest on a checking account of less than $2,500, while at least one other bank pays an interest rate on the same type checking account of 3.5 percent. Of course, the values in Panels A and B are based on the entire sample period of 2000 to 2017, which helps explain some of the substantial differences between minimum and maximum values. It is also clear that the number of observations for our outcome variables ranges from 200,000 to more than 1,600,000.

-----Insert Table 3.1-----

Table 3.2 presents correlations among the disaster exposure and bank-level variables. The disaster exposure variable is positively and significantly correlated with net interest margin, brokered deposits to total deposits, total assets, and negatively and significantly correlated with loan loss provisions to total assets. The disaster exposure variable is not significantly correlated with either ROA or the Total Risk-Based Capital Ratio.

-----Insert Table 3.2-----

Table 3.3 presents the empirical results relating to the impact of natural disasters on bank performance and bank funding. There are three panels representing three different bank performance and bank funding variables, namely ROA, Net Interest Margin (NIM) and Brokered Deposits-to-Total Deposits (BD). Results are provided for all banks as well as for banks of four different sizes. We focus on the sum of the coefficients of the disaster exposure variables due to multi-collinearity among them. Our findings indicate that the main variable of interest, disaster exposure, has a significantly positive and cumulative impact on the two performance variables and one funding variable for all banks. However, this seems to be almost entirely due to the impact of disaster exposure on these variables for just small banks.[13] In the case of mega banks, however, there is a significant positive cumulative impact only in the case of return on assets, and this is at the 10 percent significance level. In terms of economic significance for small banks, a one standard deviation increase in disaster exposure is associated with a 4 percent (3.4 basis points) increase in ROA, while, the same increase in disaster exposure is associated with a 0.6 percent (2.2 basis points) increase in NIM. As regards BD, a one standard deviation increase in disaster exposure is associated with a 9.4 percent (26.3 basis points) increase.

-----Insert Table 3.3-----

In Table 3.4, we also examine the relationship between bank performance and natural disasters before, during, and after the financial crisis, which we date from Q1 2008 to Q2 2009. The results are the same for ROA in two of the sub-periods when our entire sample period is split into the three sub-periods. More specifically, disaster exposure has a significantly positive impact on ROA for the pre-crisis and post-crisis sub-periods. However, during the crisis period, disaster exposure has a significantly negative impact on ROA. The results are essentially the same for Net

[13] In the case of ROA, we do find that disaster exposure has a significantly positive impact on ROA for mega banks at the 10 percent significant level.

Interest Margin as for ROA in terms of the three sub-periods. In the case of Brokered Deposits-to-Total Deposits, there is no significant relationship between this variable and disaster exposure.

-----Insert Table 3.4-----

So far our results indicate that natural disasters have a positive impact on both ROA and Net Interest Margin. They also indicate that natural disasters have a positive impact on the use of brokered deposits. We now examine the impact of natural disaster on both deposit and loan rates. One would expect the positive impact in the case of both these rates. However, since we find that natural disasters have a positive impact on Net Interest Margin, one would expect a bigger impact on loan rates than deposit rates. If so, this would help to explain why natural disasters have a positive impact on Net Interest Margin, and thereby ROA.

Since we find that the impact of natural disasters was combined to only all banks and small banks, we confine our additional empirical work to the causal effect of natural disasters on deposit and loan rates for those banks. Table 3.5 shows that in all cases there is a causal effect of disaster exposure on the six different interest rates. The effect is significantly positive in all cases and the increase in loan rates is always greater than the increase in deposit rates, which is consistent with our finding the disaster exposure has a positive and causal impact on net interest margin. In this table and the subsequent one, we also added the effective federal funds rate as an additional control variable, and it always entered with an expected significantly positive sign.

-----Insert Table 3.5-----

The results for small banks are reported in Table 3.6. They are essentially the same with one exception. In the case of the deposit rate for interest checking accounts with than $2,500, it is not casually related to disaster exposure. The other results also indicate that disaster exposure causally contributes to an increase in both deposit and loan rates, but the latter more than the former so that net interest margin increases.[14] Again, in terms of economic significance, a one standard deviation increase in disaster exposure is associated with 1.5 percent (10.5 basis points) increase in the auto-loan rate, a 1.7 percent (9.2 basis points) increase in the mortgage-loan rate, and 1.2 percent (9 basis points) increase in the home-equity-loan rate.

-----Insert Table 3.6-----

3.4 Conclusion

The purpose of our paper has been to examine the impact of natural disasters on bank headquarters and their branches. This is becoming ever more important as the frequency of disasters and the associated costs have increased over time. As has been discussed, there have been relatively few studies of disasters and banks. We have attempted to contribute to the studies by examining the response of the branches of banks located in areas exposed to natural disasters in terms of both deposit and loan rates. In addition, we examine the impact of the disasters on both the banks' overall performance as measured by return on assets and net interest margin as well as the extent to which banks increased their reliance on brokered deposits. Our empirical results indicate that disasters cause banks to increase deposit rates to attract more deposits and simultaneously raise loan rates due to an increase in the demand for loans. Consistently, we find that disasters also increase the return on assets and net interest margin for banks with headquarters/branches located in affected communities. At the same time, we find that banks also

[14] We consider a much wider range of interest rates and obtain essentially the same results so do not report them here.

increase their reliance on the brokered deposits as a result of the disaster-induced liquidity shortage.

3.5 Reference

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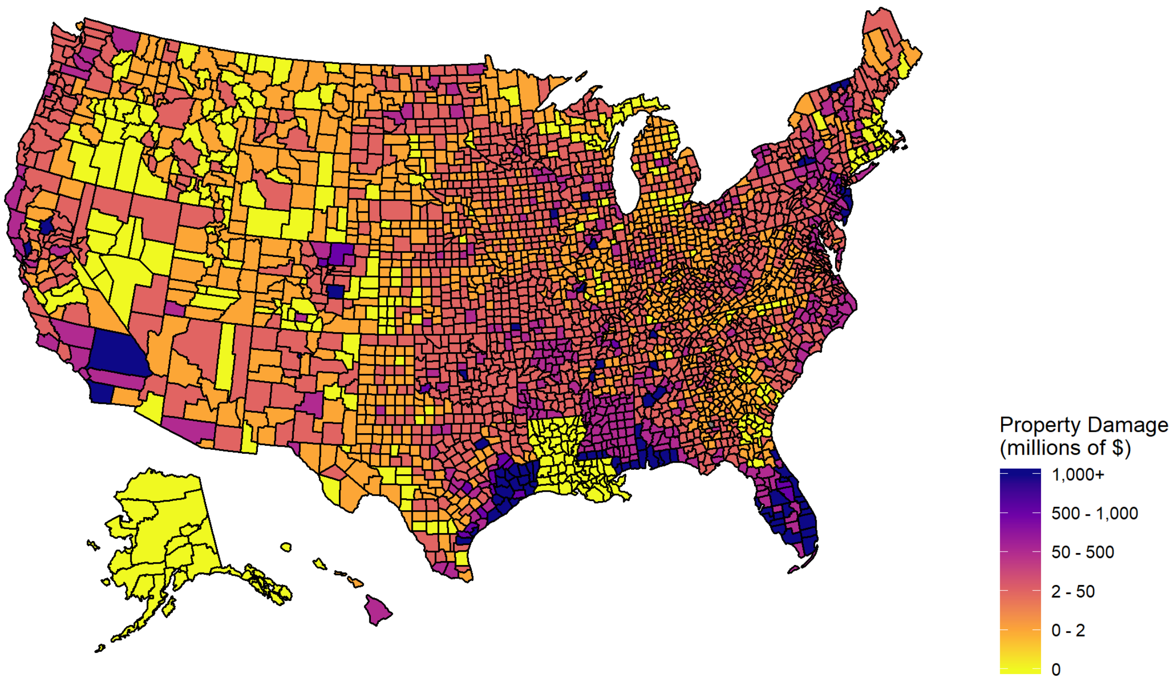
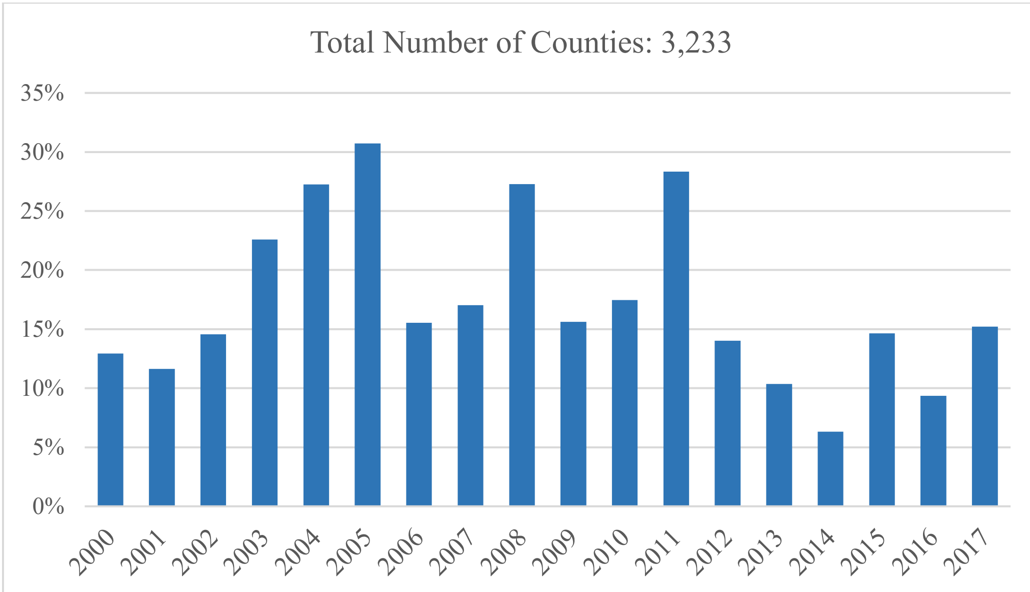
Figure 3.1
Property Damages in Counties, 2000-2017



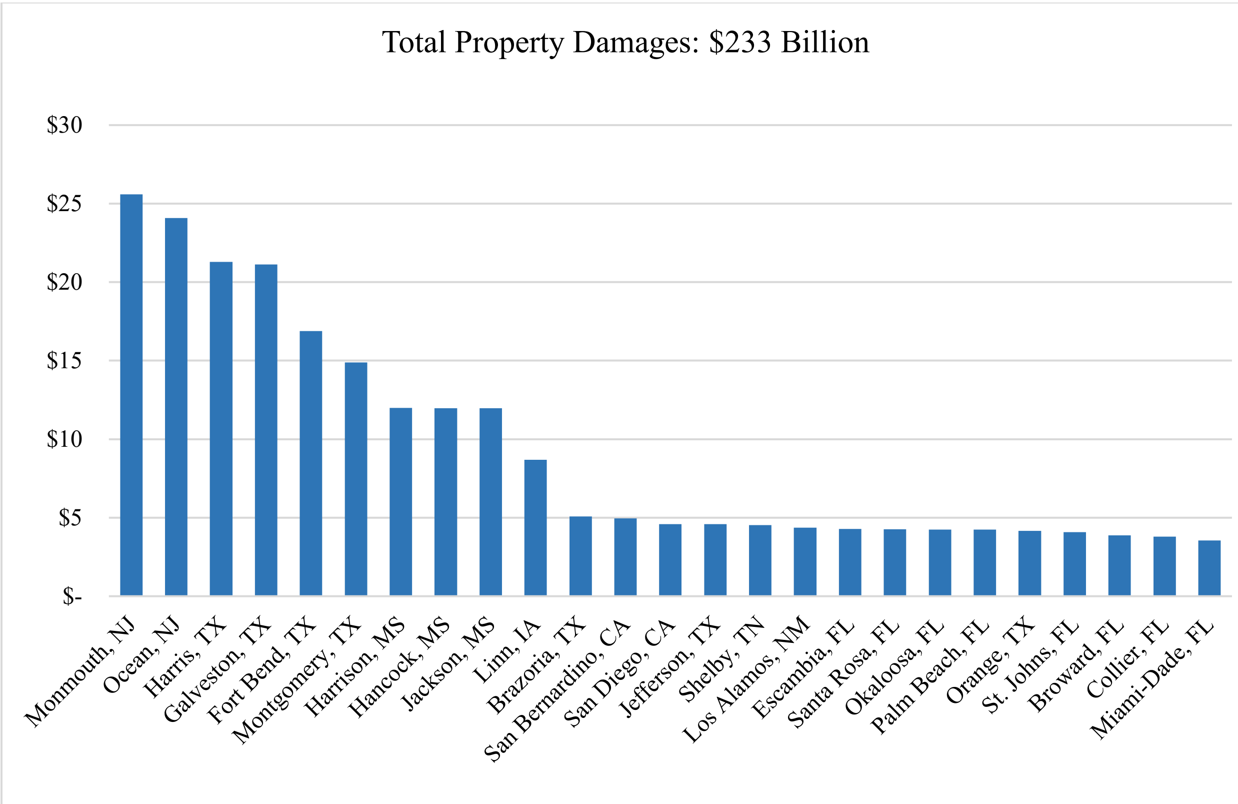
Source: SHELDUS.

Figure 3.2
Percentage of Counties with Natural Disasters



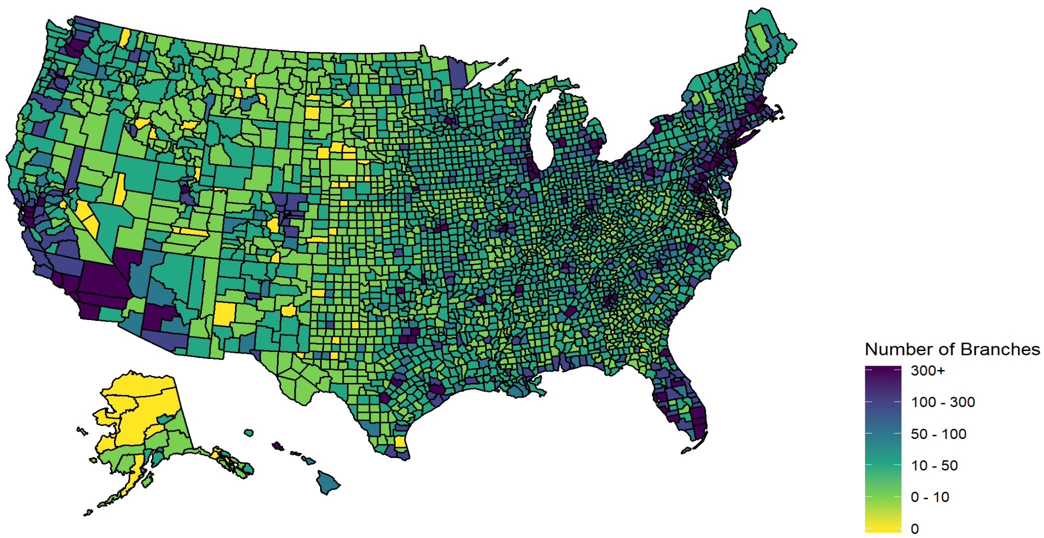
Source: SHELDUS.

Figure 3.3
Top 25 Counties: Total Property Damages from Natural Disasters, 2000-2017



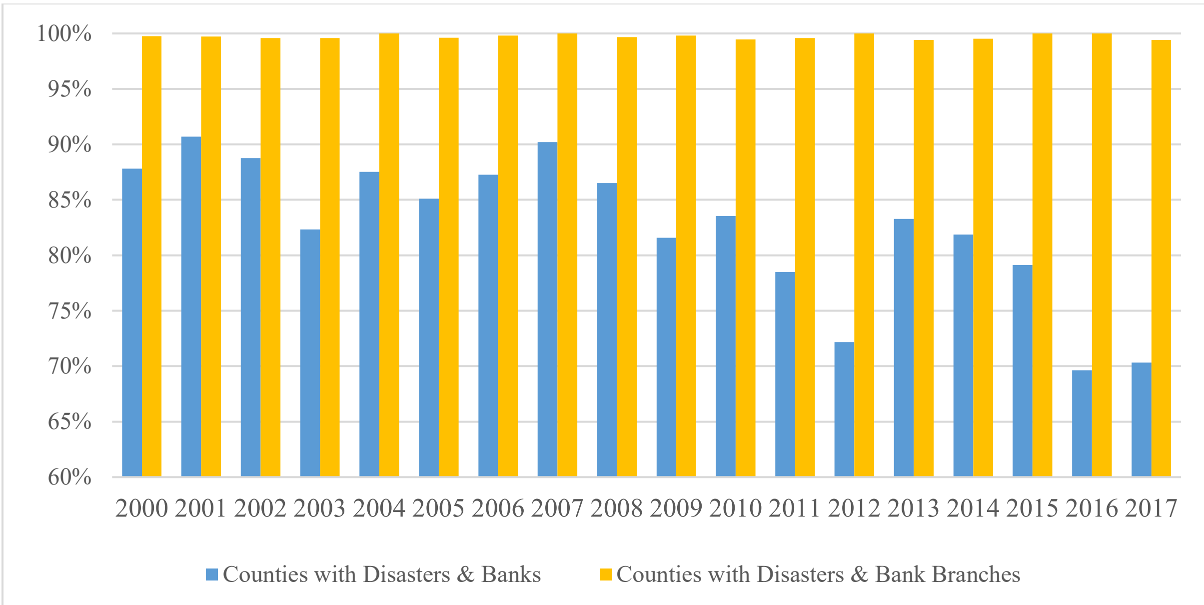
Source: SHELDUS.

Figure 3.4
Banks and Bank Branches in Counties, 2000-2017



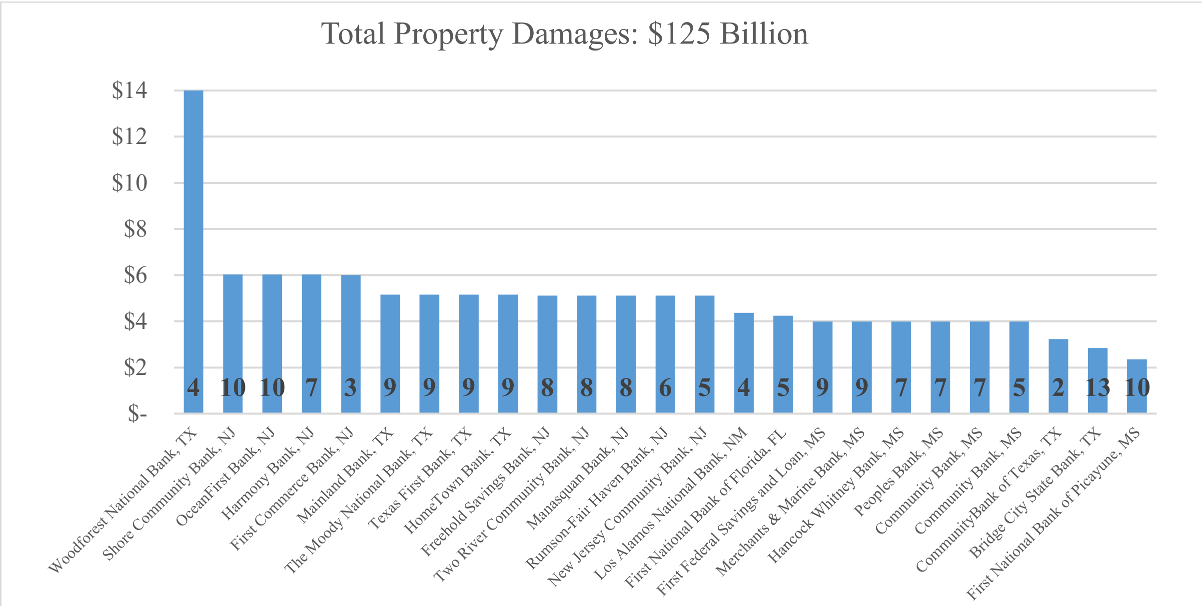
Source: FDIC.

Figure 3.5
Percentage of Counties with Both Natural Disasters and Banks/Branches, 2000-2017



Source: FDIC & SHELDUS.

Figure 3.6
Top 25 Banks: Total Property Damages and Number of Natural Disasters, 2000-2017



Source: FDIC & SHELDUS.

Table 3.1
Summary Statistics

Panel A. Bank Level Data, Quarterly

	Observations	Average	S.D.	Min.	Max.
Disaster Exposure ($ Millions)	578,168	0.05	1.91	0.00	465.59
Disaster Exposure (Ln Dollars)	578,168	0.31	1.45	0.00	18.98
ROA (%)	577,372	0.80	1.27	-7.22	6.05
Net Interest Margin (%)	577,323	3.91	0.97	0.78	8.46
Brokered Deposits-Total-Deposits (%)	578,168	0.30	0.45	0	1
Total Assets ($ Millions)	578,168	1,553	28,800	0.066	2,150,000
Ln Assets	578,168	18.85	1.40	11.10	28.40
Loan Loss Provisions to Total Assets (%)	577,372	0.30	0.81	-14.77	83.37
Total Risk-Based Capital Ratio (%)	577,367	18.89	12.35	6.84	98.60
Number of Branches	578,168	10.82	116.29	0	6,765

Panel B. Branch Deposit and Loan Rate Data, Monthly

	Observations	Average	S.D.	Min.	Max.
Auto Used 4 Yrs, 36 month term (%)	394,348	7.14	2.12	0.75	12.50
15 Yr Fxd Mtg @ 175K (%)	261,336	5.32	1.51	0.55	10.00
H.E. Loan Up to 80% LTV @ 20K - 180 Mo Term (%)	226,933	7.45	1.56	0.82	12.39
12-month CD @ $100,000 (%)	1,683,006	1.96	1.57	0.01	6.75
Interest Checking Accounts with Less Than $2,500 (%)	1,639,703	0.49	0.60	0.00	3.50
Money Market Deposit Account @ $25,000 (%)	1,631,277	1.10	1.08	0.01	13.98

Table 3.2
Correlations Among Disaster Exposures and Bank-level Variables

	Disaster Exposure (Ln dollars) (1)	ROA (2)	Net Interest Margin (3)	Brokered Deposits-Total-Deposits (4)	Ln Assets (5)	Loan Loss Provisions to Assets (6)	Total Risk-Based Capital Ratio (7)
(1)	1.0000						
(2)	0.0006	1.0000					
	(0.6593)						
(3)	0.0028	0.0440	1.0000				
	(0.0351)	(0.0000)					
(4)	0.0094	-0.0048	0.0146	1.0000			
	(0.0000)	(0.0003)	(0.0000)				
(5)	-0.0838	0.0341	-0.0159	0.1192	1.0000		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
(6)	-0.0049	-0.1786	0.0774	0.1227	0.0923	1.0000	
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
(7)	0.0006	0.0183	-0.0094	-0.0046	-0.0284	-0.0085	1.0000
	(0.6275)	(0.0000)	(0.0000)	(0.0005)	(0.0000)	(0.0000)	

Note: P-values in parentheses.

Table 3.3
Bank Performance and Natural Disasters

Panel A. ROA

	All Banks	Small Banks	Medium Banks	Large Banks	Mega Banks
Disaster Exposure$_{i,t-1}$	0.004*	0.006***	0.024	0.002	0.121
	(0.002)	(0.002)	(0.032)	(0.008)	(0.091)
Disaster Exposure$_{i,t-2}$	0.003	0.004	-0.009	-0.006	0.098
	(0.003)	(0.003)	(0.025)	(0.008)	(0.065)
Disaster Exposure$_{i,t-3}$	0.003	0.004**	-0.022	-0.003	0.136
	(0.002)	(0.002)	(0.029)	(0.007)	(0.082)
Disaster Exposure$_{i,t-4}$	0.008***	0.009***	0.029	-0.007	0.016
	(0.003)	(0.002)	(0.023)	(0.009)	(0.044)
Log Assets$_{i,t}$	0.190*	0.365***	-0.226***	-0.561***	-0.263*
	(0.113)	(0.092)	(0.082)	(0.086)	(0.151)
Loan Loss Provisions to Assets $_{i,t}$	-0.960***	-0.976***	-0.837***	-0.664***	-1.223***
	(0.021)	(0.021)	(0.062)	(0.070)	(0.435)
Total Risk-Based Capital Ratio $_{i,t}$	0.000	0.000	0.013***	-0.001***	0.005
	(0.000)	(0.000)	(0.001)	(0.000)	(0.041)
Constant	-2.424	-5.680***	6.179***	15.021***	8.552**
	(2.127)	(1.731)	(1.802)	(2.047)	(3.671)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	532,115	507,943	16,642	6,346	1,184
Adjusted R -squared	0.080	0.081	0.425	0.236	0.485
Disaster Exposure Coefficient Sum	0.018	0.023	0.022	-0.014	0.371
F-value (Sum of 12 Lags)	4.15	7.34	0.05	0.24	3.46
P-value	0.0417	0.0068	0.8179	0.6216	0.0705

Panel B. Net Interest Margin

	All Banks	Small Banks	Medium Banks	Large Banks	Mega Banks
Disaster Exposure$_{i,t-1}$	0.004***	0.004***	-0.007	0.009	0.032
	(0.001)	(0.001)	(0.016)	(0.013)	(0.023)
Disaster Exposure$_{i,t-2}$	0.003**	0.003**	-0.020	0.008	0.025
	(0.001)	(0.001)	(0.018)	(0.012)	(0.020)
Disaster Exposure$_{i,t-3}$	0.003	0.003	-0.028	-0.012	0.022
	(0.002)	(0.002)	(0.023)	(0.015)	(0.018)
Disaster Exposure$_{i,t-4}$	0.005**	0.005**	-0.001	-0.018	0.008
	(0.002)	(0.002)	(0.015)	(0.015)	(0.026)
Ln Assets$_{i,t}$	-0.288***	-0.325***	-0.351***	-0.305	-0.720***
	(0.040)	(0.047)	(0.075)	(0.228)	(0.128)
Loan Loss Provisions to Assets $_{i,t}$	0.088*	0.076	0.063	0.241***	0.354***
	(0.047)	(0.052)	(0.047)	(0.067)	(0.065)
Total Risk-Based Capital Ratio $_{i,t}$	0.000	0.000	-0.001***	-0.002**	0.011
	(0.000)	(0.000)	(0.000)	(0.001)	(0.040)
Constant	9.302***	9.951***	11.504***	10.948**	21.979***
	(0.765)	(0.896)	(1.660)	(5.448)	(3.217)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	532,079	507,907	16,642	6,346	1,184
Adjusted R -squared	0.001	0.001	0.029	0.071	0.396
Disaster Exposure Coefficient Sum	0.015	0.015	-0.056	-0.013	0.087
F-value (Sum of 12 Lags)	6.20	6.23	0.94	0.08	1.03
P-value	0.0128	0.0126	0.3333	0.7771	0.3154

Panel C. Brokered Deposits-to-Total Deposits

	All Banks	Small Banks	Medium Banks	Large Banks	Mega Banks
Disaster Exposure$_{i,t-1}$	0.105	0.105	-0.049	-0.247	0.364
	(0.070)	(0.070)	(0.154)	(0.248)	(0.277)
Disaster Exposure$_{i,t-2}$	0.024*	0.022	0.140	-0.034	0.302
	(0.014)	(0.014)	(0.188)	(0.226)	(0.248)
Disaster Exposure$_{i,t-3}$	0.030***	0.026**	0.334	0.205	0.182
	(0.011)	(0.011)	(0.314)	(0.360)	(0.155)
Disaster Exposure$_{i,t-4}$	0.031**	0.027**	0.291	0.249	0.224
	(0.012)	(0.012)	(0.355)	(0.392)	(0.192)
Ln Assets$_{i,t}$	2.658***	2.702***	3.640***	-3.051	1.254
	(0.146)	(0.114)	(0.857)	(2.747)	(1.511)
Loan Loss Provisions to Assets $_{i,t}$	0.656***	0.617***	0.534**	2.380***	0.200
	(0.066)	(0.059)	(0.222)	(0.755)	(0.454)
Total Risk-Based Capital Ratio $_{i,t}$	-0.000	-0.000	-0.011	-0.015***	-0.360
	(0.000)	(0.000)	(0.018)	(0.005)	(0.646)
Constant	-47.236***	-47.860***	-72.387***	85.904	-21.061
	(2.749)	(2.133)	(18.818)	(65.431)	(37.876)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	531,997	507,826	16,641	6,346	1,184
Adjusted R -squared	0.007	0.006	0.033	0.034	0.003
Disaster Exposure Coefficient Sum	0.190	0.180	0.716	0.173	1.072
F-value (Sum of 12 Lags)	19.29	17.62	0.64	0.03	1.69
P-value	0.0000	0.0000	0.4256	0.8697	0.2017

Note: We follow Cortés and Strahan (2017) approach to define bank size. Specifically, small banks have assets less than \$2 billion, medium banks have assets more than \$2 billion but less than \$10 billion, large banks have assets more than \$10 billion but less than \$100 billion, mega banks have assets greater than \$100 billion. Robust standard errors are presented in parentheses.

Table 3.4
Bank Performance and Natural Disasters Before, During and After Financial Crisis

	ROA			Net Interest Margin			Brokered Deposits-to-Total Deposits		
	Pre-Crisis	Crisis	Post-Crisis	Pre-Crisis	Crisis	Post-Crisis	Pre-Crisis	Crisis	Post-Crisis
Disaster Exposure$_{i,t-1}$	0.002	-0.010	0.005**	0.002	0.000	0.007***	0.119	-0.002	-0.000
	(0.002)	(0.007)	(0.002)	(0.002)	(0.001)	(0.001)	(0.112)	(0.013)	(0.007)
Disaster Exposure$_{i,t-2}$	0.003	-0.022*	0.003	0.002	-0.003	0.005***	-0.033	0.031**	0.000
	(0.003)	(0.011)	(0.002)	(0.002)	(0.003)	(0.001)	(0.033)	(0.014)	(0.006)
Disaster Exposure$_{i,t-3}$	0.006**	-0.021*	-0.002	0.007	-0.007*	0.001	-0.029	0.018	0.003
	(0.003)	(0.012)	(0.003)	(0.005)	(0.004)	(0.001)	(0.039)	(0.014)	(0.006)
Disaster Exposure$_{i,t-4}$	0.010***	-0.021**	0.007***	0.010**	-0.005***	0.002**	-0.031	0.014	0.029***
	(0.003)	(0.010)	(0.003)	(0.004)	(0.002)	(0.001)	(0.040)	(0.011)	(0.007)
Ln Assets$_{i,t}$	0.368***	1.669*	0.711***	-0.106	-0.320**	-0.106	4.414***	5.786***	2.616***
	(0.089)	(0.965)	(0.267)	(0.175)	(0.129)	(0.080)	(0.266)	(0.955)	(0.351)
Loan Loss Provisions to Assets $_{i,t}$	-0.725***	-0.996***	-0.892***	0.411**	-0.060***	0.042***	0.032	0.188***	0.766***
	(0.068)	(0.032)	(0.018)	(0.179)	(0.010)	(0.010)	(0.258)	(0.058)	(0.058)
Total Risk-Based Capital	0.000	-0.001***	0.000	0.000	-0.000***	-0.000	-0.000	0.000	-0.000
Ratio $_{i,t}$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-5.627***	-30.501*	-12.548**	5.959*	9.872***	5.737***	-79.722***	-104.290***	-46.924***
	(1.661)	(18.248)	(5.119)	(3.289)	(2.439)	(1.533)	(4.972)	(18.071)	(6.722)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	250,440	49,372	232,303	250,432	49,369	232,278	250,368	49,367	232,262
Adjusted R -squared	0.042	0.217	0.100	0.002	0.021	0.002	0.004	0.032	0.042
Disaster Exposure Coefficient Sum	0.021	-0.074	0.013	0.021	-0.015	0.015	0.026	0.061	0.032
F-value (Sum of 12 Lags)	5.74	5.30	3.23	2.94	3.00	17.64	1.03	2.34	2.16
P-value	0.0166	0.0214	0.0726	0.0865	0.0834	0.0000	0.3133	0.1257	0.1414

Note: Based upon NBER US Business Cycle Expansions and Contractions, we define financial crisis as the period of Q1 2008 to Q2 2009. Robust standard errors are presented in parentheses.

Table 3.5
Bank Deposit and Loan Rates and Natural Disasters: All Banks

	Auto Used 4 Yrs, 36 month term	15 Yr Fxd Mtg @ 175K	H.E. Loan Up to 80% LTV @ 20K - 180 Mo Term	12-month CD @ $100,000	Interest Checking Accounts with Less Than $2,500	Money Market Deposit Account @ $25,000
Disaster Exposure$_{i,t-1}$	0.018***	0.038***	0.016*	0.011***	0.003***	0.004***
	(0.007)	(0.006)	(0.009)	(0.001)	(0.001)	(0.001)
Disaster Exposure$_{i,t-2}$	0.014**	0.027***	0.019**	0.010***	0.002***	0.003***
	(0.006)	(0.006)	(0.009)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-3}$	0.019***	0.017***	0.018**	0.012***	0.001***	0.003***
	(0.006)	(0.005)	(0.009)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-4}$	0.024***	0.018***	0.024***	0.017***	0.002***	0.004***
	(0.006)	(0.007)	(0.008)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-5}$	0.020***	0.021***	0.017**	0.020***	0.002***	0.005***
	(0.006)	(0.006)	(0.008)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-6}$	0.016***	0.020***	0.012	0.021***	0.001***	0.006***
	(0.006)	(0.006)	(0.007)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-7}$	0.012**	0.012**	0.019***	0.020***	0.001***	0.005***
	(0.006)	(0.006)	(0.007)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-8}$	0.019***	0.012**	0.019***	0.019***	0.001*	0.004***
	(0.006)	(0.005)	(0.007)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-9}$	0.021***	0.016***	0.017**	0.019***	0.000	0.004***
	(0.006)	(0.005)	(0.007)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-10}$	0.011*	0.014***	0.014*	0.018***	-0.001	0.003***
	(0.007)	(0.005)	(0.008)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-11}$	0.012**	0.008	0.023***	0.016***	-0.001***	0.002***
	(0.005)	(0.006)	(0.008)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-12}$	0.023***	0.005	0.023**	0.019***	-0.001***	0.003***
	(0.007)	(0.007)	(0.009)	(0.001)	(0.000)	(0.001)
Assets $_{i,t}$	-1.013***	-0.855***	-0.397***	-0.462***	-0.294***	-0.454***
	(0.070)	(0.053)	(0.054)	(0.010)	(0.006)	(0.009)
Loan Provision to Assets $_{i,t}$	0.519***	0.279***	0.539***	0.203***	0.040***	0.113***
	(0.040)	(0.024)	(0.042)	(0.006)	(0.002)	(0.004)
Total Risk-Based Capital Ratio$_{i,t}$	-0.072***	-0.040***	-0.039***	-0.005*	0.000**	0.000
	(0.014)	(0.006)	(0.010)	(0.003)	(0.000)	(0.000)
Effective Fed Funds Rate$_{i,t}$	0.416***	0.400***	0.241***	0.666***	0.109***	0.312***
	(0.011)	(0.006)	(0.011)	(0.002)	(0.001)	(0.002)
Constant	28.298***	22.930***	15.973***	9.992***	6.102***	9.513***
	(1.507)	(1.148)	(1.253)	(0.218)	(0.129)	(0.190)
Branch Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	157,690	103,424	91,634	1,433,627	1,409,976	1,403,136
Adjusted R-squared	0.395	0.547	0.233	0.835	0.371	0.577
Disaster Exposure Coefficient Sum	0.209	0.208	0.221	0.201	0.009	0.047

F-value (Sum of 12 Lags)	12.86	13.58	7.75	905.76	4.00	43.24
P-value	0.0003	0.0002	0.0054	0.0000	0.0455	0.0000

Note: Robust standard errors are presented in parentheses.

Table 3.6
Bank Deposit and Loan Rates and Natural Disasters: Small Banks

	Auto Used 4 Yrs, 36 month term	15 Yr Fxd Mtg @ 175K	H.E. Loan Up to 80% LTV @ 20K - 180 Mo Term	12-month CD @ $100,000	Interest Checking Accounts with Less Than $2,500	Money Market Deposit Account @ $25,000
Disaster Exposure$_{i,t-1}$	0.020***	0.029***	0.017**	0.010***	0.001***	0.003***
	(0.006)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)
Disaster Exposure$_{i,t-2}$	0.015***	0.019***	0.017***	0.010***	0.001*	0.002***
	(0.005)	(0.006)	(0.006)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-3}$	0.019***	0.011*	0.017***	0.011***	0.000	0.002***
	(0.006)	(0.006)	(0.006)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-4}$	0.024***	0.015**	0.024***	0.016***	0.001**	0.004***
	(0.006)	(0.007)	(0.006)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-5}$	0.020***	0.016***	0.021***	0.019***	0.001**	0.005***
	(0.005)	(0.006)	(0.007)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-6}$	0.013**	0.015***	0.013**	0.020***	0.001	0.005***
	(0.006)	(0.006)	(0.006)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-7}$	0.010*	0.009	0.021***	0.019***	0.001	0.004***
	(0.006)	(0.006)	(0.006)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-8}$	0.016***	0.009	0.019***	0.018***	0.000	0.004***
	(0.006)	(0.006)	(0.006)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-9}$	0.019***	0.014**	0.020***	0.018***	-0.000	0.004***
	(0.005)	(0.006)	(0.007)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-10}$	0.011*	0.012**	0.016**	0.017***	-0.001***	0.003***
	(0.006)	(0.005)	(0.007)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-11}$	0.012**	0.007	0.022***	0.016***	-0.002***	0.002***
	(0.005)	(0.006)	(0.006)	(0.001)	(0.000)	(0.001)
Disaster Exposure$_{i,t-12}$	0.021***	0.001	0.022***	0.018***	-0.002***	0.003***
	(0.006)	(0.006)	(0.007)	(0.001)	(0.000)	(0.001)
Assets $_{i,t}$	-1.421***	-1.489***	-1.141***	-0.609***	-0.404***	-0.594***
	(0.109)	(0.080)	(0.127)	(0.012)	(0.008)	(0.011)
Loan Provision	0.341***	0.189***	0.264***	0.188***	0.040***	0.100***
to Assets $_{i,t}$	(0.046)	(0.028)	(0.050)	(0.007)	(0.003)	(0.004)
Total Risk-Based	-0.073***	-0.037***	-0.024**	-0.005*	0.000***	0.000*
Capital Ratio$_{i,t}$	(0.017)	(0.007)	(0.012)	(0.003)	(0.000)	(0.000)
Effective Fed Funds	0.333***	0.374***	0.224***	0.655***	0.113***	0.308***
Rate $_{i,t}$	(0.011)	(0.008)	(0.013)	(0.002)	(0.001)	(0.002)
Constant	34.907***	33.993***	29.120***	12.383***	7.926***	11.778***
	(2.174)	(1.585)	(2.574)	(0.248)	(0.152)	(0.218)
Branch Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105,114	68,637	43,308	1,136,436	1,123,227	1,111,187
Adjusted R-squared	0.325	0.541	0.281	0.831	0.401	0.592
Disaster Exposure Coefficient Sum	0.200	0.131	0.229	0.192	-0.001	0.041
F-value (Sum of 12 Lags)	12.97	6.63	7.75	817.44	0.03	29.52
P-value	0.0003	0.0101	0.0054	0.0000	0.8668	0.0000

Note: Robust standard errors are presented in parentheses.

3.6 Appendices

Table 3.A1
Counties, Counties with Disasters, and Counties with Banks, 2000 - 2017

	Counties	Counties with Disasters	Counties with Banks	Counties with Disasters & Banks	Counties with Bank Offices	Counties with Disaster & Bank Offices
2000	3,233	418	2,666	367	3,207	417
2001	3,233	376	2,638	341	3,208	375
2002	3,233	471	2,613	418	3,209	469
2003	3,233	730	2,602	601	3,208	727
2004	3,233	881	2,579	771	3,210	881
2005	3,233	993	2,552	845	3,207	989
2006	3,233	502	2,534	438	3,206	501
2007	3,233	551	2,509	497	3,207	551
2008	3,233	882	2,491	763	3,208	879
2009	3,233	505	2,464	412	3,207	504
2010	3,234	565	2,437	472	3,207	562
2011	3,234	916	2,409	719	3,207	912
2012	3,234	453	2,389	327	3,206	453
2013	3,234	335	2,366	279	3,206	333
2014	3,234	204	2,335	167	3,202	203
2015	3,234	474	2,289	375	3,203	474
2016	3,234	303	2,259	211	3,199	303
2017	3,234	492	2,222	346	3,199	489

Table 3.A2
Counties Ranked by Highest Total Damages, 2000-2017

Rank	County	State	Property Damage ($ Millions)	Number of Banks	Number of Offices
1	Monmouth	New Jersey	25,584	10	805
2	Ocean	New Jersey	24,080	5	602
3	Harris	Texas	21,300	83	2,798
4	Galveston	Texas	21,128	9	199
5	Fort Bend	Texas	16,887	7	321
6	Montgomery	Texas	14,893	4	333
7	Harrison	Mississippi	11,982	4	155
8	Hancock	Mississippi	11,980	0	36
9	Jackson	Mississippi	11,979	3	88
10	Linn	Iowa	8,693	22	174
11	Brazoria	Texas	5,073	9	166
12	San Bernardino	California	4,959	14	617
13	San Diego	California	4,596	47	1,537
14	Jefferson	Texas	4,595	3	168
15	Shelby	Tennessee	4,531	28	646
16	Los Alamos	New Mexico	4,365	1	8
17	Escambia	Florida	4,275	8	203
18	Santa Rosa	Florida	4,263	1	85
19	Okaloosa	Florida	4,248	10	235
20	Palm Beach	Florida	4,244	34	1,533
21	Orange	Texas	4,165	3	46
22	St. Johns	Florida	4,085	4	217
23	Broward	Florida	3,873	25	1,374
24	Collier	Florida	3,787	23	455
25	Miami-Dade	Florida	3,545	59	1,728
Total Damage	406,021	Sum Of 25 Counties	233,109	Percentage of Total	57%

Table 3.A3
Counties Ranked by Highest Single Damages, 2000-2017

Rank	County	State	Disaster Date	Property Damage ($ Millions)	Number of Banks (Disaster date)	Number of Offices (Disaster date)
1	Monmouth	New Jersey	10/2012	25,531	5	280
2	Ocean	New Jersey	10/2012	23,988	4	200
3	Harris	Texas	8/2017	20,001	23	967
4	Galveston	Texas	8/2017	20,000	4	74
5	Fort Bend	Texas	8/2017	16,004	0	140
6	Montgomery	Texas	8/2017	14,000	1	149
7	Hancock	Mississippi	8/2005	11,952	0	14
8	Harrison	Mississippi	8/2005	11,952	3	66
9	Jackson	Mississippi	8/2005	11,952	3	41
10	Linn	Iowa	6/2008	8,689	19	81
11	Shelby	Tennessee	5/2011	4,436	13	254
12	Los Alamos	New Mexico	5/2000	4,346	1	5
13	St. Johns	Florida	10/2016	4,083	0	64
14	Brazoria	Texas	8/2017	4,001	7	77
15	Escambia	Florida	9/2004	3,521	6	78
16	Santa Rosa	Florida	9/2004	3,521	1	34
17	Okaloosa	Florida	9/2004	3,521	7	78
18	Tuscaloosa	Alabama	4/2011	3,367	3	55
19	Collier	Florida	10/2005	3,193	9	124
20	Broward	Florida	10/2005	3,193	18	432
21	Miami-Dade	Florida	10/2005	3,193	44	585
22	Palm Beach	Florida	10/2005	3,193	16	478
23	Jasper	Missouri	5/2011	3,105	3	59
24	San Bernardino	California	10/2003	3,035	11	209
25	Jefferson	Texas	8/2017	3,000	1	50

Table 3.A4
Banks Ranked by Highest Total Damages, 2000-2017

Rank	Bank Name	County	State	Bank Headquarters/County Property Damage ($ Millions)	Number of Disasters
1	Woodforest National Bank	Montgomery	Texas	14,002	4
2	Shore Community Bank	Ocean	New Jersey	6,024	10
3	OceanFirst Bank, National Association	Ocean	New Jersey	6,024	10
4	Harmony Bank	Ocean	New Jersey	6,023	7
5	First Commerce Bank	Ocean	New Jersey	6,008	3
6	Mainland Bank	Galveston	Texas	5,161	9
7	The Moody National Bank	Galveston	Texas	5,161	9
8	Texas First Bank	Galveston	Texas	5,161	9
9	HomeTown Bank, National Association	Galveston	Texas	5,161	9
10	Freehold Savings Bank	Monmouth	New Jersey	5,116	8
11	Two River Community Bank	Monmouth	New Jersey	5,116	8
12	Manasquan Bank	Monmouth	New Jersey	5,116	8
13	Rumson-Fair Haven Bank and Trust Company	Monmouth	New Jersey	5,116	6
14	New Jersey Community Bank	Monmouth	New Jersey	5,116	5
15	Los Alamos National Bank	Los Alamos	New Mexico	4,365	4
16	The First National Bank of Florida	Santa Rosa	Florida	4,246	5
17	First Federal Savings and Loan Association	Jackson	Mississippi	3,995	9
18	Merchants & Marine Bank	Jackson	Mississippi	3,995	9
19	Hancock Whitney Bank	Harrison	Mississippi	3,993	7
20	The Peoples Bank, Biloxi, Mississippi	Harrison	Mississippi	3,993	7
21	Community Bank, Coast	Harrison	Mississippi	3,993	7
22	Community Bank, National Association	Jackson	Mississippi	3,989	5
23	CommunityBank of Texas, N.A.	Jefferson	Texas	3,232	2
24	Bridge City State Bank	Orange	Texas	2,835	13
25	First National Bank of Picayune	Pearl River	Mississippi	2,354	10

Table 3.A5
Banks Ranked by Highest Single Damages, 2000-2017

Rank	Bank Name	County	State	Number of Offices for the Bank	Number of Offices in the County for the Bank	Number of Banks in the County	Disaster Date	County Property Damage ($ Millions)
1	Woodforest National Bank	Montgomery	Texas	746	32	1	8/2017	14,000
2	OceanFirst Bank	Ocean	New Jersey	24	19	4	10/2012	23,988
3	Shore Community Bank	Ocean	New Jersey	5	6	4		
4	First Commerce Bank	Ocean	New Jersey	2	1	4		
5	Harmony Bank	Ocean	New Jersey	2	2	4		
6	Manasquan Savings Bank	Monmouth	New Jersey	8	5	5	10/2012	25,530
7	Freehold Savings Bank	Monmouth	New Jersey	2	2	5		
8	Rumson-Fair Haven Bank and Trust Company	Monmouth	New Jersey	5	5	5		
9	Two River Community Bank	Monmouth	New Jersey	18	11	5		
10	New Jersey Community Bank	Monmouth	New Jersey	3	2	5		
11	The Moody National Bank	Galveston	Texas	16	7	4	8/2017	20,000
12	Mainland Bank	Galveston	Texas	3	2	4		
13	HomeTown Bank, National Association	Galveston	Texas	7	5	4		
14	Texas First Bank	Galveston	Texas	22	13	4		
15	Los Alamos National Bank	Los Alamos	New Mexico	3	2	1	5/2000	4,346
16	The Peoples Bank, Biloxi, Mississippi	Harrison	Mississippi	17	11	3	8/2005	23,904
17	Merchants & Marine Bank	Jackson	Mississippi	11	10	3		
18	Hancock Bank	Harrison	Mississippi	51	21	3		
19	First National Bank of Lucedale	Jackson	Mississippi	3	2	3		
20	First Federal Savings and Loan Association	Jackson	Mississippi	4	5	3		
21	Community Bank, Coast	Harrison	Mississippi	4	3	3		
22	The First National Bank of Florida	Santa Rosa	Florida	8	4	1	9/2004	3,521
23	CommunityBank of Texas, N.A.	Jefferson	Texas	34	6	1	8/2017	3,000
24	First National Bank of Picayune	Pearl River	Mississippi	6	5	1	8/2005	2,331
25	Reliance Bank	Limestone	Alabama	5	5	1	4/2011	2,218

Table 3.A6
Banks Ranked by Highest Single Damages, 2000-2017, Use Office to Count Damage

Rank	Bank Name	County	State	Disaster Date	County Property Damage ($ Millions)
1	Hancock Bank	Harrison	Mississippi	8/2005	13,516
2	Wells Fargo Bank, National Association	Minnehaha	South Dakota	8/2017	10,721
3	JPMorgan Chase Bank, National Association	Delaware	Ohio	8/2017	9,533
4	Wells Fargo Bank, National Association	Minnehaha	South Dakota	10/2012	6,354
5	Woodforest National Bank	Montgomery	Texas	8/2017	6,334
6	Bank of America, National Association	Mecklenburg	North Carolina	10/2012	5,840
7	Compass Bank	Jefferson	Alabama	8/2017	5,774
8	Sovereign Bank, National Association	New Castle	Delaware	10/2012	5,767
9	Bank of America, National Association	Mecklenburg	North Carolina	8/2017	5,238
10	The Peoples Bank, Biloxi, Mississippi	Harrison	Mississippi	8/2005	5,158
11	Regions Bank	Jefferson	Alabama	8/2005	4,832
12	PNC Bank, National Association	New Castle	Delaware	10/2012	4,551
13	TD Bank, National Association	New Castle	Delaware	10/2012	4,511
14	Prosperity Bank	Wharton	Texas	8/2017	4,306
15	Whitney National Bank	Orleans	Louisiana	8/2005	3,966
16	ZB, National Association	Salt Lake	Utah	8/2017	3,929
17	Texas First Bank	Galveston	Texas	8/2017	3,873
18	JPMorgan Chase Bank, National Association	Delaware	Ohio	10/2012	3,455
19	Bank of America, National Association	Mecklenburg	North Carolina	9/2004	3,111
20	BancorpSouth Bank	Lee	Mississippi	8/2005	3,056
21	First National Bank Texas	Bell	Texas	8/2017	2,980
22	Merchants & Marine Bank	Jackson	Mississippi	8/2005	2,928
23	OceanFirst Bank	Ocean	New Jersey	10/2012	2,648
24	Capital One, National Association	Fairfax	Virginia	8/2017	2,484
25	Wachovia Bank, National Association	Mecklenburg	North Carolina	9/2004	2,469